Empirical Investigations of Current Monetary and Fiscal Policy Issues

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List of Acronyms

ADF	Augmented Dickey-Fuller test
AIC	Akaike information criterion
AMECO	Annual macro economic database of the European Commission
ARIMA	Autoregressive integrated moving average
AG	Ausführungsgesetz zu Artikel 53 der Verfassung des Landes Schleswig-Holstein
AKS	Arbeitskreis Steuerschätzungen
BCB	Brazilian Central Bank
BIC	Baysian (or Schwarz) information criterion
BRL	Brazilian Real
BIP	Bruttoinlandsprodukt
BMF	Bundesministerium der Finanzen
BMWi	Bundesministerium für Wirtschaft und Energie
CFE	International conference on computational and financial econometrics
CV	Common variation
DFG	Deutsche Forschungsgemeinschaft
DGF	Deutsche Gesellschaft für Finanzwirtschaft
DStatG	Deutsche Statistische Gesellschaft
EA	Euro area
ECB	European Central Bank
ECM	Expectation conditional maximization algorithm
EM	Expectation maximization algorithm
EMBI	Emerging market bond index
EMH	Efficient market hypothesis
EU	European Union
EUROSTAT	Statistical office of the European Union
EFV	Eidgenössische Finanzverwaltung
EU Kommission	Europäische Kommission
FFR	Federal funds rate
FX	Foreign exchange
FAG	Finanzausgleichsgesetz
GDP	Gross domestic product
GLS	Generalized least squares

GG	Grundgesetz für die Bundesrepublik Deutschland
HP	Hodrick, Prescott filter
HST	Hirshleifer, Subrahmanyam, Titman model
IA	Internet Appendix
LR	Likelihood ratio
LV	Landesverfassung des Landes Schleswig-Holstein
ML	Maximum likelihood
MHP	Modifizierter Hodrick, Prescott Filter
NAWRU	Non-accelerating wage rate of unemployment
OECD	Organisation for Economic Co-operation and Development
OF	Order flow net position
OLS	Ordinary least squares
OTC	Over the counter
PBM	Portfolio balance model
PC	Principal component
PCA	Principal component analysis
PSPP	Public sector purchase program
RMSE	Root mean squared error
SELIC	Brazilian Central Bank overnight rate
SIC	Schwarz (or Baysian) information criterion
SISBACEN	Datacenter of the Brazilian Central Bank
SVAR	Structural vector autoregressive model
SVR	Sachverständigenrat zur Begutachtung der gesamtwirtschaftlichen Entwicklung
StabG	Gesetz zur Förderung der Stabilität und des Wachstums der Wirtschaft
US	United States
USD	United States Dollar
VAR	Vector autoregressive model
VECM	Vector error correction model
VIX	Chicago board options exchange volatility index

Chapter 1

Introduction

This dissertation comprises four empirical, third-party funded, unpublished working papers. The first two contributions are in the field of monetary policy and stability in international financial markets. These papers make use of recent methodological advances in statistical causality analysis between multiple economic variables of interest. One particular merit of statistical identification is that it offers an estimate of causal linkages without *a priori* restrictions by employing data features like (un)conditional heteroscedasticity or non-normality. This is in contrast to earlier approaches, where, e.g., specific causal linkages between variables of interest are ruled out pre analytically. However, statistical identification approaches are not limited to, but well suited for financial market data as under study in this thesis.

In the first two papers I investigate causal interactions, i.e. financial market workings as well as changes to them in policy episodes. Subsequently, the empirical pattern of interactions is used to discriminate between competing finance theories. Thus, not only the effectiveness of central bank policy is revealed, but also the answer to the question how the policy action under study works in detail given disentangled empirical causalities.

Moreover, the first paper provides methodological contributions to the literature on the statistical identification of structural vector autoregressive (SVAR) models, which may also be applied to structural vector error correction models (SVECM). That is, I show that in the presence of unconditional heteroscedasticity model parameters may be completely estimated and exactly identified in closed form. The particular merits are at least threefold. Firstly, the proposed iterative procedure rests on reduced form estimation. Once convergence of parameters is reached structural parameters are obtained by matrix decompositions. In this the proposed estimation procedure is more stable than iterative structural estimation as, e.g., suggested in Lanne and Lütkepohl (2008).[1] This is the case since depending on the number of simultaneous equations several observationally equivalent structural parameter representations exist. However, this potentially leads to problems in numerical optimization. Secondly, estimation procedures in closed form typically require less computational time. Finally, the proposed procedure may raise the acceptance of statistical identification among practitioners, since it is very similiar to classical SVAR estimation techniques.

[1] The list of references for each paper is attached at the end of each chapter right after the corresponding conclusions.

The latter two papers incorporated in this thesis are dedicated to the field of fiscal policy and public finance. The questions under study here are relevant for the European Stability and Growth Pact and, e.g., have consequences for the German federal as well as for state public budget constraints.[2] In this part I concentrate on the evaluation of competing statistical procedures and structural econometric models for estimation and forecasting of unobservable economic variables like potential growth and long-term tax incomes.
We show that using real time data of both the observable gross domestic product (GDP) and tax incomes, e.g., for the structural potential growth model of the European Commission one may employ classical statistical inference procedures to evaluate estimates and forecasts of unobservable economic long-term developments.
This way we extend government reporting standards in fiscal planning (point estimates and forecasts) of the latter variables for model specific uncertainty stemming from data revisions over time. That is, we contribute to the discussion by proposing a model evaluation based on the criterion of public budget uncertainty as measured through forecasting errors and resulting density forecasts (fan charts). In doing so decision makers can discriminate between different methodologies for unobservable potential growth and long-term tax forecasting on the basis of historical deviations from planned and realized figures. The need for such criteria is given since methodological adjustments, e.g., for the structural potential growth model of the European Commission are made on a regular basis. However, the implications of these changes for public budget uncertainty are not monitored yet. Clearly, the idea of stable, frictionless budgets and sustainable public spendings are the central aim of the European Stability and Growth Pact.

Chapter 2

The first paper of this thesis is entitled "On interdependence and shift contagion between core Euro Area (EA) refinancing conditions".
The first objective of this paper is to reveal linkages between EA bond markets that exist due to economic integration. Based on this pattern the relative importance of crossmarket transmissions of EA member specific news for the long-term refinancing conditions of other EA members are obtained. Moreover, we document structural shifts in linkages as triggerd by the Euro crisis as well as by the announcement of the President of the European Central Bank to do what ever it takes to preserve the Euro from failure, e.g., by buying debt as done under the public sector purchase program (PSPP). Clearly, with this action the European Central Bank (ECB) is trying to bring down high yields of southern EA members. However, apart from the question of whether government debt should be bought at all, the revealed causality pattern may guide to an optimal PSPP strategy with respect to EA yield convergence and low yield levels. This strategy may then take into account both direct and indirect stabilizing effects.
I concentrate on linkages between EA core bond markets consisting of Germany, France, Italy and Spain. Noteably, these countries stand for approximately 80% of the ECB paid-up capi-

[2] Since these papers may be of special interest to the German public they are written in German. However, as for the other parts of this dissertation an extended abstract in English is provided as part of chapter 1.

tal and ECB bond purchases from EA members, respectively. That is, from a disaggregated inspection of PSPP purchases I find evidence for the bond basket currently held by the ECB to be weighted in line with liabilities of EA members as relative to their paid-up capital.
To evaluate structural linkages and changes between EA bond market yields I employ an SVAR framework and identify instantaneous causalities, i.e. news transmissions through unconditional heteroscedasticity. This way one obtains structural linkages without imposing *a priori* restrictions on the underlying causalities. As already noted above this paper methodologically contributes to the identification literature by proposing an estimation procedure in closed form as close as possible to traditional SVAR estimation techniques. For this purpose I simplify the estimation procedure for unconditional heteroscedastic data proposed in Lanne and Lütkepohl (2008). That is, in line with traditional SVAR techniques, estimation of reduced form parameters can be done in a first step followed by a structural identification step, where the latter rests on reduced form covariance matrix decomposition.
The main findings of this paper are as follows. Prior to the Euro crisis French bond market news provide an anchor for yield pricing of the complete EA core. That is, French news are the main source of yield variation for all core EA countries under investigation. In contrast, home market news especially for the southern countries play a subordinate role or no role. In the Euro crisis this anchor is lost. Instead, I find bonds are priced on a less granular level. That is, especially the importance of country specific home market news increases. I see this as evidence for distrust in the Euro (Maastricht process) triggered by the Greek debt crisis. Moreover, I find southern bond market news are the source of observed divergence in yields. The ECB announcement to preserve the Euro was only partially effective in reestablishing pre crisis linkages. The French anchor is reestablished. However, distrust in the Euro (Maastricht process) is not fully removed, e.g., home market news remain an important driver of yields. An optimal ECB buying strategy based on the provided causalities may take into account both direct and indirect stabilizing effects. For example, in the current period I find buying Spanish bonds has an additional indirect stabilizing effect on Italian bond markets. Moreover, given the current yield levels buying Spanish bonds leads to convergence of EA core yields. However, buying French bonds lowers yields and hence improves the long-term refinancing conditions of the complete EA core.

This paper is single-authored. The paper has been accepted at the following conferences: 11th International Conference on Computational and Financial Econometrics (CFE 2017). For this paper the author gratefully acknowledges financial support by *Deutsche Forschungsgemeinschaft* (DFG: HA 5391/2-1).

Chapter 3

The second paper of this thesis is entitled "FX pricing and strategic trading".
In this paper we investigate the workings of speculative markets in matching demand and supply. That is, the interplay of both trading strategies of security seekers (speculators) and price setting rules of large liquidity providers (market makers) are endogeneously modeled.

This way, on the one hand we examine the informational content of prices and the information diversity reflected in prices as well as market liquidity (depth) and stability. On the other hand trading strategies and performance of distinctly and privately informed groups of traders are simultaneously discovered. Moreover, we evaluate the effects of policy interventions on both foreign exchange (FX) trading and pricing.
The market under study is the Brazilian Real / U.S. Dollar FX market, where 100 % of the end-user order flow (trade) record is available for six years on a daily basis. Moreover, order flows are disaggregated by transaction motive. That is, excess demand positions are available for underlying trades in assets versus trades in goods as well as for FX interventions. Finally, the data under study embodies a natural experiment since the central bank is only intervening in the first half of the sample under investigation.
As in multiperiod strategic trading models ala Kyle (1985) we assume subsets of liquidity seekers are endowed with group individual private information signals about the future price development. Hence, these groups try to profit through trading on these distinct signals. In turn, uninformed liquidity providers need to learn private information from the total trade record to quote appropriate clearing prices.
In contrast to arbitrageurs, speculators take risky positions to generate profits and thus want to reduce exposure in a timely manner. Thus, once they observe favorable price moves speculators may start reverting their positions already in the short run. Todays the lion's share of volume in equity as well as foreign currency markets is generated from high frequency trading. That is, due to informational surprises it is possible to both manage positions and to revise price quotes within seconds or even shorter periods of time.
To account for these issues we suggest the following methodological contributions. Firstly, we introduce a Normal Mixture VAR model and statistical identification to the market microstructure literature. More specifically we show that by exploiting state dependent covariance matrices we can allow for instantaneous feedback trading of speculators. That is, contemporaneous position reversals due to price movements are not ruled out by *a priori* assumptions. Secondly, employing the same data features we can allow for instantaneous learning between asset and goods traders again without any *a priori* restrictions. That is, both trader groups may obtain the other groups signal instantaneously, e.g., through the trading process. Thirdly, as common in the microstructure literature we do not rule out instantaneous market maker quote revisions due to information arrivals. Finally, the statistical model and the data features employed are in line with the Mixture of Normals Hypothesis. Thus, from a theoretical viewpoint conditional heteroscedasticity used for identification exists due to differences in the rate of information arrival leading to differences in trade intensities. As a consequence empirical results may be presented conditional on trade intensity states.
The main findings of the paper are as follows. As a consistent finding in intervention and no-intervention times asset traders are early informed speculators as compared to goods traders. In the no-intervention period asset traders are able to take advantage of their early informedness through a short-term profit-taking strategy. That is, we present evidence for instantaneous feedback trading of asset traders due to favorable price moves. Moreover, we find strategy performance is excellent since 70% of asset trade variation is due to price changes.

Thus, asset traders are able to open positions and to take profits and reduce exposure during the same trading day. In contrast, goods traders learn from financial orders and in doing so display a follow-the-leader strategy. That is, they take counterpart positions for and hence share risk with asset traders. Moreover, we find a stable price informativeness across trade intensity states. That is, private information accounts for a majority of 70% of FX price variation. In turn, public information explains only 30%. We interpret this finding as evidence for a mature FX market with a fairly constant number of participants. However, information diversity depends on trade intensities. Since intensities of both groups develop inversely we provide evidence for strategic substitutability. That is, a higher trade intensity from the financial sector comes along with a lower intensity from goods traders and vice versa. Moreover, if trade intensity from the asset trading dimension is high these surprises explain 70% of FX price variation alone. If it is low asset trades explain 52%, while informational surprises from goods trading explain the remaining 18%.
The picture is different in intervention times. Firstly, goods traders exhibit an instantaneous positive feedback trading strategy. Thus, market makers are not able to unload inventory risk on end-users and hence liquidity risk rises. Moreover, prices may drift away from fundamentals. The central bank intervenes in the market. We find interventions do not affect FX prices directly. Instead, two indirect intervention channels are established, both targeting asset traders. Firstly, trade intensities of asset traders and the central bank show strategic complementarity, i.e. they switch together from high to low states, while at the same time FX price variation is dampened with higher trade intensities. Moreover, as also predicted by the theory we observe that asset trades have no price impact in intervention times. Instead, asset traders act as pure liquidity providers. As a consequence we find a comparable low and poor price informativeness and information diversity reflected in prices. Secondly, asset traders instantanously trade in the same direction as the central bank. As a result of this signalling channel intervention costs are reduced. Thus, central bank interventions substantially improve market liquidity, but come at the implicit costs of higher uncertainty about underlying price fundamentals.

This paper is co-authored with Markus Haas. My contribution consists of the entire literature research, programming and larger parts of the writing. Part of the writing in chapter 3.4 was done by Markus Haas. The authors would like to thank Maria Gelman, Vasyl Golosnoy, Helmut Herwartz, Stefan Mittnik, Emanuel Moench, Stefan Reitz and Lucio Sarno as well as the participants at several conferences and seminars for helpful comments and suggestions. Earlier versions have been accepted and presented at the following conferences: 23rd Annual Meeting of the German Finance Association (DGF 2016), Annual Meeting of the German Statistical Society (DStatG 2015) and 9th International Conference on Computational and Financial Econometrics (CFE 2015). For this paper the authors gratefully acknowledge financial support by *Deutsche Bundesbank*.

Chapter 4

The third paper of this thesis is entitled "Evaluation of the German fiscal surveillance process and enhancement of the production function methodology of the EU Commission".
Since 2016 the Federal Republic of Germany has committed itselve by constitutional law to limit newly issued debt to 0.35 percent of GDP in the long run. However, to stabilize macroeconomic developments in the short run by countercyclical fiscal policy stimulus the federal constitution allows the issuing of new debt in excess to this number in recession times, which in turn must be reduced one-to-one in boom times.
The major problem which arises in practical implementation of this public budget constraint is the estimation of a 'normal economic development', i.e. the measurement of unobservable potential output and GDP deviations from these figures over the business cycle. Moreover, public budgets need to be approved ex ante, i.e. for future fiscal periods. As a result one additionally needs to produce forecasts of GDP and potential output. For the former the Federal government relies on its own methodology and forecasts, while for the latter the production function methodology of the European Commission is employed. For the observable GDP, the evaluation of forecast performance is straight forward. However, this is not the case for unobservable variables like potential growth. As a consequence forecasting performance is not part of the reporting standard of the EU Commission nor of the Federal government of Germany yet.
I contribute to the discussion by using real-time data for GDP provided by the European Commission together with historical GDP forecasts of the Federal government of Germany to evaluate the ex post performance of both Federal government GDP and potential growth forecasts from the production function methodology of the EU Commission as well as for alternative models for potential growth. Using real-time data, it is possible to assess the influence of statistical GDP and forecast revisions on model specific potential growth forecasting uncertainty. Since the latter translates into public budget uncertainty different approaches for modelling potential growth may be ranked accordingly. Moreover, reporting standards are enriched through fan charts depicting forecast uncertainty of potential output and future adjustments of the methodology can be evaluated based on the proposed criterion.
The main findings of this paper are as follows. In the period under investigation year-to-year Federal government GDP forecast revisions indicate conservative forecasts. That is, future GDP is systematically underestimated ex ante. As a consequence the structural debt component used in fiscal planning is underestimated too. In a szenario approach comparing forecasting performances for potential output of the Federal government over the medium term the current approach of the EU Commission is inferior to a simple Hodrick Prescott (HP) Filter from the following fiscal year until the end of the fiscal planning horizon. That is, our results suggest for each current fiscal year the production function approach of the EU Commission has lower forecasting uncertainty than the HP Filter, while from the up coming year onwards to the end of the medium term fiscal planning horizon HP Filter forecasts of potential output produce smaller public budget revisions.

This paper is single-authored. For this paper the author gratefully acknowledges financial support by *Fritz-Thyssen-Stiftung*.

Chapter 5

The fourth paper of this thesis is entitled "Evaluation and methodological advances in estimation and forecasting of long-term tax incomes for Schleswig-Holstein".
The aim of this paper is to evaluate alternative methodological procedures for the estimation and forecasting of business cycle adjusted tax incomes for Schleswig-Holstein. These figures are relevant for fiscal planning of the State government. Next to existing law the desired procedures were requested to fulfill objectivity and transparency and to keep the administrative burden low. Like for the Federal government, tax forecasts for Schleswig-Holstein are revised on a biannual basis. Thus, procedures were asked to deliver an endogeneous adjustment of trend taxes to an extended information basis over the fiscal year. Moreover, tax forecasts need to be extended until the end of the long-term fiscal planning horizon, e.i. until ten years in the future.
Given the above requirements forecasting of aggregate tax incomes beyond the medium term is done by employing an ARIMA model. To keep the administrative burden low we concentrate on statistical filters for trend estimation and forecasting. We propose employing tax income data and medium term forecasts historically used for fiscal planning between 2000 and 2012 to evaluate candidate filters by their specific revision sensitivity in tax trends due to an extended information basis. Evaluation is done utilizing root mean squared deviations between long-term tax developments in the short and medium run as estimated on the basis of ex ante trend forecasts in comparision to the ex post tax trend as estimated on the latest information basis.
The main findings are as follows. The HP Filter delivers smaller revisions in long-term taxes for Schleswig-Holstein than a modified version employed by the Federal financial administration of Switzerland. This result holds true for the short term as well as for the medium term planning horizon. Moreover, both evaluated versions of the HP Filter are in line with the State constitution of Schleswig-Holstein. Thus, the standard version is recommanded since it delivers more stable ex ante forecasts of long term tax incomes and hence more stable public budgets for the State of Schleswig-Holstein and its subordinate corporations.

This paper is co-authored with Markus Haas. My contribution consists of the literature research, programming and larger parts of the writing. Writing of extended explanations in chapter 5.4 were done by Markus Haas. This paper is written and designed as a State government report by order of the *Ministry of Finance, Schleswig-Holstein*.

Chapter 2

On interdependence and shift contagion between core euro area refinancing conditions

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Abstract

We evaluate changes in linkages between Euro Area (EA 12) country long-term bond yields since the introduction of the Euro in January 2001. These linkages are measured as instantaneous cross market transmissions in a structural vector autoregressive (SVAR) framework. This way we document interdependence, shifts and break-ups in structural relationships of core EA countries. Moreover, the relative importance of country specific news for the refinancing conditions of others are revealed. We test for changes in pricing rules in the Euro crisis period and find the ECB announcement to buy and mutualize government debt was only partially effective in reestablishing pre crisis interdependencies.

Keywords: Bond markets, Euro crisis, interdependence, shift contagion, statistical identification, unconditional heteroscedasticity.

JEL classification: C32, C54, C58, G12, G14, G15

2.1 Introduction

Before the introduction of the Euro as a deposit currency in January 2001, later EA countries committed themselves in Maastricht treaty to fulfill economic convergence measured by some hard criteria. Among these criteria refinancing conditions of EA members are of enduring interest to market participants and policy makers.
However, in January 2001 Greece joint the EA 11 after the country officially fulfilled Maastricht convergence. The development of the EA 12 series together with some important events is depicted in Figure 1.

Starting with the Greek debt crisis in mid of December 2009 a widening of the spreads of the

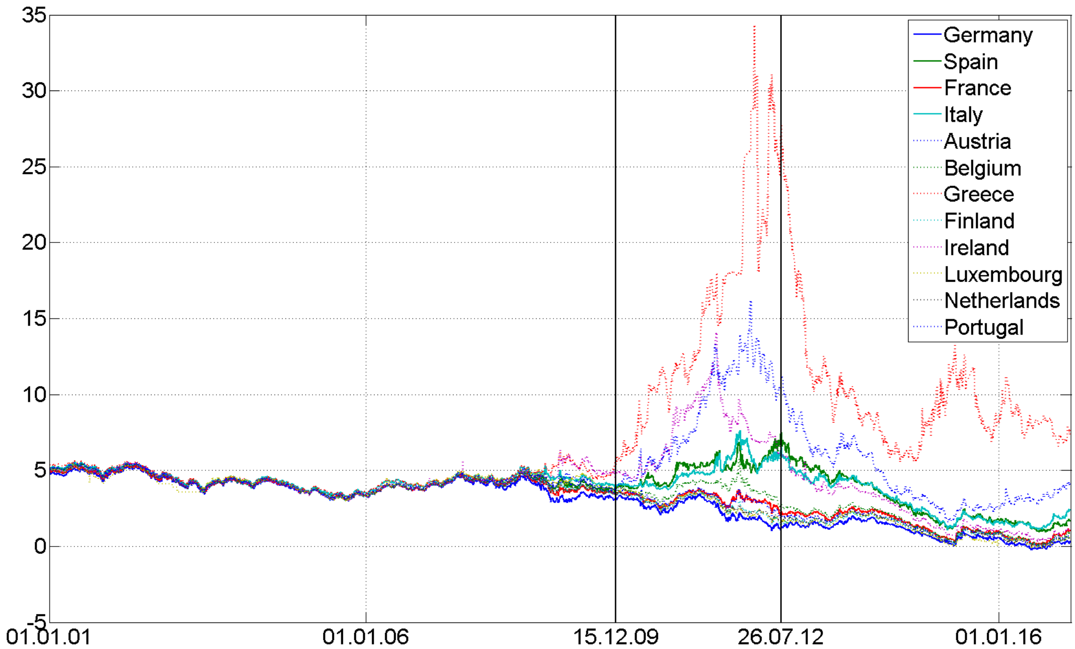

FIGURE 1: Development of EA 12 countries 10-year-to-maturity government bond-yields in percent points p.a. for the period 01/01/2001 to 22/02/2017. *Source*: EUROSTAT, convergence criteria series.

EA member countries vis-a-vis Germany has been observed. At this time markets received a common signal from a rating downgrade by Standard and Poors that Greece had not actually fullfilled Maastricht convergence. Undoubtedly, this event lead to higher market uncertainty (volatility) and had the potential to change the rules how to correctly price not only Greek, but EA country debt.
However, in a famous speech by Mario Draghi on 26th of July 2012, the president of the ECB announced "(...) the ECB is ready to do whatever it takes to preserve the Euro. And believe me, it will be enough. (...)" and especially to buy any amount of government bonds to stabilize the Euro Area (reestablish convergence). With this step the ECB tried to fill the

gap that was produced by to few fiscal policy reforms.[1] Clearly, the ECB announcement to buy and hence mutualize EA government debt was a turning point in ECB policy and again may have changed not only market volatility, but EA debt pricing rules.

Table 1a (see appendix) displays a ranking of the ECB capital paid-up by the current EA members (column four) together with the cumulative purchases of the public sector purchase program (PSPP) of the ECB (column two). As can be inferred from the table on the 31st of March 2017 the ECB already bought government bonds with a current book value of 1.481 trillion Euro in total, while it had paid-up capital from the national central banks of the EA of 7.62 billion Euro. In column three we calculated relative purchases of EA government debt and in column five the relative capital key (EA members only), respectively.

Interestingly, from these columns we observe that the current ECB strategy is to buy a basket of EA government bonds where weights are broadly in line with the relative paid-up capital of the member countries.[2] Thus, one of our objectives is to evaluate the effectiveness of this ECB strategy with regard to convergence of long-term refinancing conditions as observed in pre crisis times.

The starting point of our empirical investigation is the event study approach in Forbes and Rigobon (2002) and the methodologies proposed in Rigobon (2003). Following the former we take an indirect approach for disentangling what is defined as interdependence versus shift contagion linkages. Interdependencies between countries or markets, e.g., as the result of economic integration are then measured in non crisis periods. In contrast, shift contagion refers to both quantitative or qualitative structural change in crisis times.

For example, after a financial market event one may find amplified cross market transmissions or even new linkages between markets. In line with crisis contingent theories these changes are interpreted as changes in market pricing rules (See, e.g., Rigobon 2001 for a survey).

However, for our empirical analysis it is crucial to destinguish between events leading to changes in or even new linkages between markets and pure variance changing ones, respectively. As demonstrated in Forbes and Rigobon (2002) estimates of cross market linkages need to be corrected for differences in volatility around the considered event. In other words one needs to correct estimates of interdependence and shift contagion for pure scaling effects from differences in volatility. We take this idea into account in a multivariate SVAR model for EA government bond yields.

Moreover, in contrast to Forbes and Rigobon (2002) we are heading for a structural perspective. That is, we are interested in the causal directions of (inter)-dependencies and the relative importance of single core EA member news for others refinancing conditions. For this purpose we adopt the methodologies in Rigobon (2003) and apply and simplify the iterative estimation procedure proposed in Lanne and Lütkepohl (2008).[3]

One particular merit of statistical identification approaches is to achieve an unrestricted estimate of instantaneous cross country transmissions. For this purpose variance shifts are used as probabilistic instruments to exactly identify otherwise stable structural relationships. That

[1] https://www.ecb.europa.eu/press/key/date/2012/html/sp120726.en.html

[2] Small differences may occur due to rounding in ECB publications.

[3] That is, for exactly identified parameters we show estimation may be done completely in closed form.

is, to allow for differences in the latter we split our sample and estimate structural linkages before and after possible pricing rule changing events such as the start of the Euro crisis and the ECB announcement. Afterwards we test for changes in this pattern.

Moreover, we employ principal component analysis (PCA) as a statistical dimension reduction technique and extract common factors from periphery EA country yields. These common unobserable components are then used to control for common heteroscedastic shocks in an SVAR model of core EA countries. Since principal components display common movements in yields they are often related to underlying bond fundamentals like global or local macroeconomic developments.

For example, Ang and Piazessi (2003) show in a yield curve VAR model that common unobservable components loose their explanatory power once inflation and industrial production growth are included. They argue that multicollinearity is the reason. Based on their evidence we see common components of periphery yields as possible proxies for macroeconomic developments and use them in an SVAR of core EA countries.[4] We define the core countries as Germany, France, Italy and Spain according to the ranking of ECB paid-up capital and cumulative bond purchases from Table 1a. Noteably, these four countries together stand for approximately 80% of the paid-up capital and ECB bond purchases.

The objective of our empirical investigation is close to DeGrauwe and Ji (2013). They provide evidence from panel regressions of spreads from several EA countries vis-a-vis Germany, e.g., France, Italy and Spain among others to be disconnected from underlying fundamentals like debt-to-GDP ratio, real effective exchange rates or GDP growth in the period from 2008:Q1 to 2011:Q3. Moreover, they find spreads to be mainly driven by shifts in mean measured through time dummies. In contrast, they find large parts of the spread variation from Greece, Portugal and Ireland is explained by their respective fundamentals. That is, depending on the loadings of our common components a second interpretation emerges. If single countries yield variation is responsible for the lions share of common component variation the corresponding component may be interpreted as local, country specific rather than as a global macroeconomic one.

Indeed, we find the composition of principal components of periphery countries differ markedly between crisis and non crisis times. During non crisis times all yields load quite equally on the first component. Thus, we interpret this one as a proxy for global fundamentals as a common driver of EA yields. However, after the start of the Euro crisis the first two PCs are dominated and solely loaded on by the local developments in Greece, Portugal and Ireland. That is, we find the local developments in those countries dominate common periphery yield variation. This finding is in line with DeGrauwe and Ji (2013) and we find it persists after the ECB announcement.

Moreover, the ECB announcement was only partially successfull in reestablishing pre crisis interdependencies between core EA countries. However, our unrestricted estimate of structural

[4] Again an indirect approach is taken since macroeconomic variables are typically available only on rather low frequencies. In contrast, the statistical identification procedures employed build on asymptotic inference and thus their validity profits from using daily rather than monthly or quarterly data. Moreover, without controlling for common shocks structural relationships may be overestimated (c.f. Forbes and Rigobon 2002 and Rigobon 2003).

linkages may be exploited in an ECB buying strategy when low yield levels and convergence is the objective. This strategy then takes into account both direct and indirect stabilizing effects.

The rest of the paper is structured as follows. Section 2.2 introduces the data and how interdependence and shift contagion are measured in a structural framework. Additionally, the employed econometric procedures in estimation, identification and inference are highlighted. In section 2.3 the empirical results are discussed. Finally, section 2.4 provides concluding remarks.

2.2 Empirical assessment

This section describes the yield data under investigation as well as the model framework and the procedures used in estimation and inference. Moreover, special emphasis is placed on assumptions for statistical identification schemes as well as on alternative structural parameter representations.

2.2.1 Data

Daily government bond yield data for EA 12 countries are drawn from Eurostat's Maastricht (convergence) criteria series. The countries under investigation are Austria, Belgium, Germany, Spain, Finland, France, Ireland, Italy, Luxembourg, Netherlands, Portugal and Greece. We define Germany, Spain, France and Italy as the EA core countries and the remaining countries as periphery. The data contains secondary market yields p.a. for government bonds of ten years to maturity. The sample period runs from 01/01/2001 to 22/02/2017. Excluding non trading days we have a total of $T = 3620$ observations. Our subsamples S_i for $i = 1, ..., 3$ are choosen according to the beginning of the Euro crisis and the ECB announcement. That is, we measure interdependence in the non crisis period S_1 running from 01/01/2001 until 14/12/2009. As the start for the Euro crisis period S_2 we choose 15/12/2009 according to a rating downgrade for Greece by Standard and Poors until 25/07/2012, i.e. one day before the ECB announcement. The last subsample S_3 constitutes the period following the ECB announcement which runs from 26/07/2012 until 22/02/2017. The yields in level exhibit non-stationary properties, while the first differences are stationary processes (see Figures 2 to 4, Appendix A). These properties are confirmed by ADF tests for all yield series and subsamples. The analysis is done in first differences of the data.[5]

Next to the principal components estimated from the periphery country yields we control for US government bond yields p.a. with a maturity of 10 years as another common shock to the core countries under investigation. US yields are also incorporated in first differences and are drawn from Datastream.

[5]We also performed cointegration tests for the core yields in levels. Johansen trace tests delivered no evidence for cointegration in S_2 and S_3, while in S_1 there is evidence for core yields being cointegrated. However, since we are interested in a comparison of the short term dynamics we stick to the VAR framework in all subsamples for reasons of comparability.

2.2.2 General model framework

Our empirical SVAR framework rests on the approaches in Rigobon (2003) and Lanne and Lütkepohl (2008), which we apply to a $K \times 1$ vector of first differences in core EA bond yields $\boldsymbol{y}_t = (Germany_t, Spain_t, France_t, Italy_t)'$ as,

$$\boldsymbol{y}_t = \boldsymbol{\nu} + C(L)\boldsymbol{y}_{t-1} + D(L)\boldsymbol{z}_{t-1} + \boldsymbol{B}\epsilon_t, \tag{2.1}$$

where $\boldsymbol{\nu}$ is a vector of constants, $C(L)$ and $D(L)$ are $K \times K$ parameter matrices of lagged endogeneous variables $\boldsymbol{y}_t$ and (predetermined) exogeneous controls $\boldsymbol{z}_{t-1}$ with L being the lag operator.
The matrix $\boldsymbol{B}$ is of major interest in our analysis since it governs the instantaneous cross market transmissions of structural country specific bond market news ϵ_t, where $\epsilon_t \sim (0, \Sigma_\epsilon)$ and Σ_ϵ is diagonal. Thus, structural innovations ϵ_t are uncorrelated. However, for a feasible estimation the SVAR in (2.1) is typically estimated in reduced form,

$$\boldsymbol{y}_t = \boldsymbol{\nu} + C(L)\boldsymbol{y}_{t-1} + D(L)\boldsymbol{z}_{t-1} + u_t \tag{2.2}$$

and the identification problem arisis since

$$u_t = \boldsymbol{B}\epsilon_t, \tag{2.3}$$

where countries instantaneous yield reactions summarized in the rows of $\boldsymbol{B}$ are implicit to the reduced form innovation vector $u_t \sim (0, \Sigma_u)$. Typically, one has to draw back on economic theory or a priori knowledge for identification of the structural relationships (see, e.g., Fry and Pagan 2007, Uhlig 2005, Faust 1998, Gali 1992 or Blanchard and Quah 1989). However, all of these procedures achieve identification through restrictions on the parameter space – for example by imposing zero restrictions on parameters in $\boldsymbol{B}$. These restrictions are neccessary to match the number of freely estimated parameters and the number of covariance equations in Σ_u. Moreover, just like for all identification procedures a certain ordering of endogeneous variables needs to be assumed. In absence of a generally accepted body of theory on interdependence and contagion we prefer a different approach.
Statistical identification schemes take a different view on the problem in that they increase the number of covariance equations available for parameter identification. We make use of the identification scheme in Rigobon (2003) and Lanne and Lütkepohl (2008). Under the prerequisite of at least two regimes of unconditional heteroscedasticity this scheme is able to exactly identify an unrestricted matrix $\boldsymbol{B}$. Suppose the sample period between two linkage changing events runs from $t = 1, ..., T$ with just one change in variance at point T_B and $1 < T_B < T$, then

$$E[u_t u_t'] = \begin{cases} \Sigma_{u1} & \text{for} \quad t = 1, ..., T_B - 1, \\ \Sigma_{u2} & \text{for} \quad t = T_B, ..., T, \end{cases} \tag{2.4}$$

where Σ_{u1} and Σ_{u2} are reduced form covariance matrices in variance regime $r = 1, 2$, respectively. These two covariance matrices can now be simultaneously decomposed as $\Sigma_{u1} = \boldsymbol{BIB}'$ and $\Sigma_{u2} = \boldsymbol{B}\Omega\boldsymbol{B}'$ (see, Golub and van Loan 1989) with structural variance parameters summarized as relative variance estimates in $\Omega = diag(\omega_i)$ for $i = 1, ..., K$ and all $\omega_i > 0$. This way the parameters in $\boldsymbol{B}$ are interpreted as the instantaneous response to a unit shock in regime 1, since $\Sigma_{\epsilon 1} = I_K$, but may be easely rescaled to a unit shock in regime two by post-multiplying $\boldsymbol{B}$ with $\Omega^{1/2}$.
Moreover, the following three assumptions need to be fulfilled for an (exact) identification. Firstly, the matrix of instantaneous parameters $\boldsymbol{B}$ must be stable (up to rescaling). Secondly, shifts in structural variances between regimes are not proportional, i.e. $\omega_i \neq \omega_j$ for all $i \neq j$. Finally, innovations ϵ_t are orthogonal in both regimes, which is a standard assumption is SVAR analysis.
If these assumptions are satisfied, the resulting matrix $\boldsymbol{B}$ is locally unique. That is, unique up to changes in column signs and ordering. For the former this means matrix $\boldsymbol{B}$ displays symmetry to negative and positive unit shocks. For the latter, columns of $\boldsymbol{B}$ may be exchanged in an observationally equivalent way. That is, to achieve complete identification we order columns in $\boldsymbol{B}$ in such a way that the main diagonal elements display the largest response in absolute value. In other words, we asign the largest impact in absolute value to be the impact of a countries own shock. As a result cross market transmissions are all smaller than respective home market responses, which is the most conservative view we can think of in an analysis of interdependence and contagion.
However, as pointed out by Forbes and Rigobon (2002) it is crucial to compare linkage parameters free from any scaling effects. In our structural multivariate set-up this may be reached by an alternative simultanoeus decomposition which restricts the main diagonal parameters in $\boldsymbol{B}$ to a unit impact. That is, we can write equation (2.3) observationally equivalent, as

$$u_t = \boldsymbol{B}^* \Lambda_r^{\frac{1}{2}} \epsilon_t, \qquad (2.5)$$

where differences from variances are seperated from the linkage parameters in $\boldsymbol{B}^*$. In this case now $\Sigma_{u1} = \boldsymbol{B}^* \Lambda_1 \boldsymbol{B}^{*'}$ and $\Sigma_{u2} = \boldsymbol{B}^* \Lambda_2 \boldsymbol{B}^{*'}$. Thus, one obtains unrestricted estimates for structural regime variances $\Lambda_r = diag(\lambda_{ir})$ for $r = 1, 2$ and $i = 1, ..., K$. Further decomposition details are provided in Appendix C.

2.2.3 Estimation and inference

For the identification scheme drawn above it is necessary to estimate reduced form innovations u_t and covariance matrices from the system in (2.2), where regressors of all equations are numerically the same. Hence, an equation-wise ordinary least squares estimation (OLS) of the system is feasible even with correlated innovations $u_t = (u_{1t}, u_{2t}, u_{3t}, u_{4t})'$ (see, Zellner 1962). To determine the optimal lag length we employ the consistent Schwarz criterion (SIC) in our analysis.
We follow the iterative estimation procedure in Lanne and Lütkepohl (2008) and point out some short-cuts for the case of exact identification in the following. With reduced form

innovations available from OLS we calculate the estimates of the regime covariance matrices out of (2.4),

$$\hat{\Sigma}_1 = \frac{1}{T_B - 1} \sum_{t=1}^{T_B - 1} \hat{u}_t \hat{u}_t' \quad \text{and} \quad \hat{\Sigma}_2 = \frac{1}{T - T_B + 1} \sum_{t=T_B}^{T} \hat{u}_t \hat{u}_t'. \tag{2.6}$$

In a second step simultaneous decomposition can be achieved by maximizing the following concentrated log-likelihood function with respect to all elements of $\boldsymbol{B}$ and Ω,

$$\begin{aligned} log\ l = & -\frac{T_B - 1}{2}(log|\boldsymbol{B}\boldsymbol{B}'| + tr[\hat{\Sigma}_1(\boldsymbol{B}\boldsymbol{B}')^{-1}]) \\ & -\frac{T - T_B + 1}{2}(log|\boldsymbol{B}\Omega\boldsymbol{B}'| + tr[\hat{\Sigma}_2(\boldsymbol{B}\Omega\boldsymbol{B}')^{-1}]). \end{aligned} \tag{2.7}$$

This way one obtains estimators $\hat{\boldsymbol{B}}$ and $\hat{\Omega}$ for $\boldsymbol{B}$ and Ω, respectively. To account for the assumed pattern of heteroscedasticity we employ a feasible generalized least squares (GLS) estimation after the second step, where we iterate between the optimization of the log likelihood function in (2.7) and a GLS estimation of the model in (2.2) until convergence of parameters in $\hat{\boldsymbol{B}}$ and $\hat{\Omega}$ is reached. This way one obtains heteroscedasticity robust parameter estimates and standard errors. The latter can be drawn from the inverse of the Hessian of (2.7). Of course, these estimators are only Gaussian quasi-maximum likelihood estimators, since we are not assuming normality here. However, these procedures remain asymptotically valid under more general distributional assumptions as pointed out by Lanne and Lütkepohl (2008).

However, in the case of exact identification one may estimate the model completely in closed form. For this purpose one iterates between the GLS estimation of the system in (2.2) and the reduced form covariance estimate from (2.6) until the reduced form parameters of the system in (2.2) have converged. That is, the model may in the first step be estimated completely in reduced form using OLS in the first iteration and GLS afterwards to control for heteroscedasticity. In a second step reduced form covariances may be simultaneously decomposed to obtain estimates of the structural parameters $\hat{\boldsymbol{B}}$ and $\hat{\Omega}$ or $\hat{\boldsymbol{B}}^*$ and $\hat{\Lambda}_1$, $\hat{\Lambda}_2$. Corresponding standard errors may again be obtained from the Hessian of (2.7).[6] Technical details how to obtain $\hat{\boldsymbol{B}}$ and $\hat{\Omega}$ or $\hat{\boldsymbol{B}}^*$ and $\hat{\Lambda}_1$, $\hat{\Lambda}_2$ are given in Appendix C.

We think it is worth pointing out this alternative since it shows the great similarities to standard identification procedures. For example, when assuming a lower triangular matrix $\boldsymbol{B}$ this is reached by a Cholesky decomposition of a single reduced form covariance matrix. Moreover, iterative estimation of reduced form parameters turns out to be more stable than iterative structural parameter estimation proposed in Lanne and Lütkepohl (2008). This is the case, since for structural parameters in $\boldsymbol{B}$ and $\boldsymbol{B}^*$ there exist several observationally equivalent column orderings, which may differ between iterations.

To access the identifying assumption of a change in variance Lanne and Lütkepohl (2008)

[6] Since, in (2.7) we can observationally equivalent reparametrize $\boldsymbol{B}\boldsymbol{B}' = \Sigma_{u1} = \boldsymbol{B}^*\Lambda_1\boldsymbol{B}^{*'}$ and $\boldsymbol{B}\Omega\boldsymbol{B}' = \Sigma_{u2} = \boldsymbol{B}^*\Lambda_2\boldsymbol{B}^{*'}$.

suggest using an LR test in reduced form for no regime change with the following pair of hypotheses,

$$H_0: \ \Sigma_1 = \Sigma_2 \qquad H_1: \ \Sigma_1 \neq \Sigma_2, \tag{2.8}$$

where H_0 specifies the hypothesis of no regime change, i.e. $\Omega = I_K$. We can test here in reduced form, because the structural form cannot be stable, if the reduced form is not (see also, Candelon and Lütkepohl 2001). The corresponding test statistic λ_{LR} is given as:

$$\lambda_{LR} = (T_1 + T_2) log|\hat{\Sigma}_{1,2}| - T_1 log|\hat{\Sigma}_1| - T_2 log|\hat{\Sigma}_2| \sim \chi^2(q), \tag{2.9}$$

where T_1 and T_2 are the number of observations in regime one and two. Let the separately estimated reduced form innovations of the full-sample and the two sub-samples be $\hat{u}_t$, $\hat{u}_t^{(1)}$, $\hat{u}_t^{(2)}$, then $\hat{\Sigma}_{1,2} = T_1^{-1} \sum_{t=1}^{T_1} \hat{u}_t \hat{u}_t' + T_2^{-1} \sum_{t=T-T_2+1}^{T} \hat{u}_t \hat{u}_t'$, $\hat{\Sigma}_1 = T_1^{-1} \sum_{t=1}^{T_1} \hat{u}_t^{(1)} \hat{u}_t^{(1)'}$ and $\hat{\Sigma}_2 = T_2^{-1}$ $\sum_{t=T-T_2+1}^{T} \hat{u}_t^{(2)} \hat{u}_t^{(2)'}$ describe the corresponding covariance matrices over the full-sample, the first sub-sample and the second sub-sample, respectively. The degrees of freedom for this LR test equal the number of constant reduced form parameters under H_0. If the Null can be rejected there is evidence for a regime change in structural variances.

However, as one can easily see by reformulation of the hypothesis in terms of the structural form this test is not able to disentangle pure variance changing events from changes in cross market transmissions. Thus, the validity of this test for our identifying assumption tested is at least limited.

As a consequence, we also employ a battery of Wald tests for the structural variances to test whether there are enough pieces of identifying information from heteroscedasticity. For these tests the hypotheses are:

$$H_0: \omega_i = \omega_j \qquad H_1: \omega_i \neq \omega_j \tag{2.10}$$

for $i = 1, ..., K$ and all $i \neq j$. The Wald test statistic is given as:

$$\lambda_{Wald} = (R\hat{\theta} - r)'[R\widehat{\Sigma}_\theta R']^{-1}(R\hat{\theta} - r) \sim \chi^2(q), \tag{2.11}$$

with $\hat{\theta}$ as the vector of estimated parameters from (2.7). R is a restriction vector and r is a scalar both corresponding to H_0. $\widehat{\Sigma}_\theta$ is the estimated covariance matrix of the parameters in θ. The degrees of freedom q of a Wald test are equal to the number of linear restrictions under H_0. If the H_0 can be rejected, the two tested ω_i are distinct from one another. If the Nulls for the LR test and Wald tests are rejected, there is evidence in favor of enough identifying information from heteroscedasticity.

As pointed out by Forbes and Rigobon (2002) to test for a structural change in cross market transmissions it is crucial to compare linkage parameter estimates free of scale. We again rely on Wald tests, where we test for differences in single parameters in $\boldsymbol{B}^{S*}$ for periods $S = 1, ..., 3$ corresponding to our samples S_1 to S_3. Moreover, due to symmetry one needs to specify whether to compare positive or negative impacts. We test single cross market transmission parameters in $\boldsymbol{B}^{S*}$ where the main diagonal is restricted to a unit impact of a positive shock in all subsamples. That is, we test the hypothesis of no change in cross market linkages as estimated from the interdependence sample S_1 against linkage parameters estimated after the start of the Euro crisis (S_2) and after the ECB announcement to preserve the Euro (S_3), respectively. However, this test is valid whether or not the disturbance variances are the same as long as the parameter estimators steem from independent samples and both are consistently estimated and asymptotically normally distributed (c.f., e.g., Greene 2003). The pair of hypothesis for these tests are given by,

$$H_0 : \boldsymbol{B}_{ij}^{1*} = \boldsymbol{B}_{ij}^{l*} \qquad H_1 : \boldsymbol{B}_{ij}^{1*} \neq \boldsymbol{B}_{ij}^{l*} \tag{2.12}$$

for $i \neq j$, where $i, j = 1, ..., K$ and $l = 2, 3$ since we are interested in changes from in the interdependence pattern S_1 against S_2 and S_3, respectively. The Wald test statistic is given as:

$$\lambda_{Wald} = (R\hat{\theta} - r)'[R\widehat{\Sigma}_{\theta}^{(1)}R' + R\widehat{\Sigma}_{\theta}^{(l)}R']^{-1}(R\hat{\theta} - r) \sim \chi^2(1), \tag{2.13}$$

with $\hat{\theta} = (\hat{\theta}^{(1)}, \hat{\theta}^{(l)})'$ as the vector of estimated parameters from (2.7) for subsamples S_1 and S_l. Again, R is a restriction vector and r is a scalar both corresponding to H_0. $\widehat{\Sigma}_{\theta}^{(1)}$ is the estimated covariance matrix of the parameters in $\theta^{(1)}$ and $\widehat{\Sigma}_{\theta}^{(l)}$ for $\theta^{(l)}$, respectively.
If the H_0 can be rejected, there is evidence for a break in structural relationships between interdependence and crisis times, which may be interpreted as evidence for shift contagion in EA government bond yields.

2.3 Results

In this section the empirical results are presented and discussed. We start with the reduced form evidence followed by structural results. For the latter we begin with a discussion of structural interdependencies in non crisis times and shift contagion in the follow-up periods. Finally, evidence on changes in the relative importance of cross country transmissions are given.

2.3.1 Reduced form evidence

We start our discussion with the reduced form evidence. That is, firstly we consider the principal components results for the EA periphery yield covariances in the interdependence sample S_1 compared to the period S_2 after markets received a common signal about Greece not fulfilling Maastricht convergence and the period after the ECB announcement S_3, respectively. These results are summarized in Table 1. As can be seen in the table, the first two principal components together explain 69.46% and the first component alone 52.98% of the yield variation of periphery countries in S_1. Moreover, we find the first component explains a nearly equal share of the yield variation of our eight considered periphery countries. In that we interpret and label this one as a global (macroeconomic) fundamental component. Interestingly, the second component which still explains 16.48% of the yield variation is majorly loaded on by one single country, i.e. this component explains 84.00% of the Luxembourg yield variation.

Turning to sample S_2, we find the first two principal components together now explain 93.91% and the first component alone is now responsible for 83.64% of the variation. Additionally, this first principal component now explains 99.64% of the Greece yield variation. Thus, the first component is not a global one, but local and country specific, which is responsible for 83.64% of the variation in periphery yields. Moreover, the second component is dominated by the local developments in Portugal and Ireland, where it explains 78.87% and 20.35% of the yield variation of the respective countries. Hence, in S_2 principal components of periphery yields are constituted differently and thus may also be labeled in a different way. Interestingly, the first two components in S_2 and S_3 are comparable in all aspects. That is, we do not find any evidence from principal components analysis of the periphery yields for an effective ECB announcement.

Table 2a, 2b, 2c for samples $S_1, ..., S_3$ respectively summarize reduced form VAR estimates for Germany, Spain, France and Italy, where we include the first two principal components and first differences in U.S. long-term yields as predetermined control variables.[7]

As can be seen from the regressions in Table 2a the first component is significant in all equations in S_1. That is, periphery yield variation is a common driver of core country yields only in the interdependence period. However, as noted above the first component is very differently loaded. In S_1 it is a global component, while in S_2 and S_3 it reflects the variation in Greek yields alone. Moreover, in S_1, i.e. in Table 2a the impact of the first component is positive for all core countries indicating a procyclical behavior of core EA and periphery yields, which may be expected for a global fundamental component.

The second component is only significant for Germany in S_1 regressions in Table 2a, while in S_2 and S_3 it is only significant for Spain and Italy (c.f. Tables 2b and 2c). Again the loading of the second component is different in S_1 compared to S_2 and S_3, respectively. In S_1 the variation of the second component is majorly explained by the variation in Luxembourg yields. In contrast, in S_2 and S_3 its variation steems from Portuguese and Irish yields. Interestingly, signs of the parameters change between the Euro crisis period and the ECB announcement period. That is, in S_2 yields from southern European core countries move in the same direction as the periphery yields (c.f. Table 2b), while in S_3 negative signs suggest an inverse development in line with capital migrations from the periphery to the southern core countries (c.f. Table 2c).

The impact of changes in the U.S. long-term refinancing conditions are displayed in the last row of Tables 2a, 2b and 2c. During the interdependence period we observe positive comovements between all core countries and U.S. yields (c.f. Table 2a). However, as depicted in Table 2b, starting with the Euro crisis improving U.S. refinancing conditions lead to higher Spanish and Italian yields. Moreover, in S_3 after the ECB announcement these parameters turn insignificant at a 5% level (c.f. Table 2c). Hence, we see a decoupling of the southern core countries from U.S. developments after the ECB announcement to preserve the Euro.

[7]The SIC criterion favored a lag length of one in S_1, S_2 and a length of two in S_3. However, for reasons of comparability we present results for $p = 2$ in all three samples.

Table 3 closes the reduced form result discussion and gives first pieces of evidence for our statistical identification to be successfull. That is, as proposed in Lanne and Lütkepohl (2008) we perform an LR test for no change in reduced form variances for a known break point T_B according to the pair of hypothesis in (2.8). As can be inferred from the table, the Null of no change is rejected in all subsamples S_1 to S_3. However, Wald tests for equality of structural variances ω_i may give more convincing evidence for a change in structural variances needed for statistical identification of structural shocks.

2.3.2 Tests on identifying assumptions

Table 4 presents estimates of regime two structural variances in Ω which are estimated relatively to the first regime for samples S_1 to S_3 together with their corresponding standard errors. We use this relative estimate to evaluate the assumption of non proportional changes in structural variances as a prerequisite for our statistical identification procedure – that is, to count the number of probabilistic instruments available in comparison to the number of structural parameters estimated in $\boldsymbol{B}$ and Ω or $\boldsymbol{B}^*$, Λ_1, Λ_2. However, as noted above these two representations are observationally equivalent in the two regime case and the exact choice depends on the aim of the empirical investigation.
Table 5 provides Wald test results for changes in variances around the pure variance changing events T_B. For an exact statistical identification we need to reject the Null of equality for all structural variance shifts within every sample S_1 to S_3. As can be inferred from the p-values in the last column of Table 5 this is the case for all common significance levels. Thus, we are allowed to interpret our structural cross market transmissions for the interdependence sample S_1 and follow-up periods S_2 and S_3.

2.3.3 Structural interdependencies

Table 6 summarizes cross country transmissions of a positive unit impact home market shock for the periods S_1 to S_3. If not mentioned otherwise we describe the effects of positive shocks in the following. Since we ordered the columns in $\boldsymbol{B}$ such that the main diagonal displays the column-wise largest parameters in absolute value off-diagonal parameters in $\boldsymbol{B}^*$ are all smaller than a unit impact displayed on the main diagonal. That is, we take a conservative view and assume instantaneous cross country responses are smaller than the respective home market response.
The interdependence pattern is summarized in $\boldsymbol{B}^*$ of sample S_1, i.e. $\boldsymbol{B}^{1*}$ of Table 6. As can be seen significant interdependence parameters have mostly positive signs, i.e. cross country refinancing conditions develop in the same direction to shocks from Germany and France displayed in the first and third column. Thus, in the interdependence sample we find mostly cross market transmissions leading to positively related yield developments which may be plausible for homogeneous, integrated economies as suggested by fulfilled Maastricht convergence criteria.

Interestingly, France is the only economy that is linked with all other core countries. That is, shocks to France are transmitted positively to all other countries. This result is in line with France providing an anchor for core country debt pricing meaning long term refinancing conditions of the EA core develop in the same direction as France yields.
However, positive shocks to Italy lead to negative cross market responses, where especially the effect on Germany of -0.726 is quite high compared to -0.34 for France. We interpret this finding as evidence for financial markets not fully believing in Maastricht convergence in the case of Italy. Consequently, worsening refinancing conditions for Italy induce capital migrations to Germany and to a lesser extent also to France. That is, we see causal portfolio reallocations initiated by Italian shocks already in the interdependence sample S_1.

2.3.4 Structural shifts in the Euro crisis period

Matrix $\boldsymbol{B}^{2*}$ in Table 6 summarizes cross market linkages in the Euro crisis period, where widening spreads have been observed in Figure 1. As can be inferred from the third column of $\boldsymbol{B}^{2*}$ in comparison to the same column in $\boldsymbol{B}^{1*}$, France lost its anchor function for core EA debt pricing. That is, although cross market responses of Spain and Italy to a shock on France remain relatively stable compared to S_1 corresponding linkages between France and the rest of the core economies appear now insignificant at a 5 % level. Thus, we see some evidence for a decoupling of EA core yields from France developments.
Instead we find two new significant linkages suggesting positively related yield developments in the group of southern versus northern core members. Firstly, a positive unit impact on Germany leads to a positive cross market response of France, i.e. shocks on Germany are now important for French yield pricing. Secondly, in contrast to the interdependence period S_1 Spanish shocks now have a positive effect on Italian yields. These latter two effects are also confirmed by our test results for structural change presented in Table 7. That is, in S_2 we find isolated comovements for Germany and France and for the group of southern members Italy and Spain, respectively.
In contrast, positive shocks on Spain have a significant negative impact on German yields in S_2 compared to a negative and insignificant impact in S_1.[8] Moreover, negative cross market responses of Italian shocks on Germany are significantly lower in S_2 (c.f. Table 7), but survive in the Euro crisis period. Finally, from inspection of Table 6 as well as Table 7 we find a decoupling of France from Italian shocks. That is, in contrast to S_1, worsening refinancing conditions for Italy do not induce capital migration to France. Instead, worsening refinancing conditions for the southern core members Spain and Italy both induce capital flows to the German bond market only.
Thus, in the Euro crisis period S_2 we find the following structural shifts in pricing rules and capital flows between EA core countries compared to the interdependence sample S_1. Firstly, France lost its anchor function for EA debt pricing. Secondly, we see concerted developments in yields between on the one hand northern and on the other hand southern members, re-

[8] However, formal tests for structural change in Table 7 suggest no difference in these parameter estimates.

spectively. Thirdly, Germany's refinancing conditions react inversely to southern core country yield shocks. That is, given the level of EA core yields our results suggest southern bond market news are the source of shocks leading to widening spreads vis-a-vis Germany as observed in Figure 1.

2.3.5 Structural shifts after the ECB announcement

Finally, we come to the discussion of structural relationships in the period after the ECB announcement to preserve the Euro S_3. A credible announcement to buy EA member debt in case markets do not believe in economic convergence should *ceteris paribus* lead to a reestablishment of the interdependence pattern. Estimates for $\boldsymbol{B}^{3*}$ are again given in Table 6, while formal test results for no structural change between the interdependence pattern from S_1 compared to S_3 are summarized in Table 8.

From the third column of $\boldsymbol{B}^{3*}$ compared to $\boldsymbol{B}^{1*}$ given in Table 6 we infer that France provides an anchor for EA government debt pricing in both periods. That is, in contrast to the Euro crisis period core EA country yields develop in the same direction as French yields again. However, positive cross market transmissions of French shocks to Italy of 0.918 are higher compared to 0.711 in S_1. These findings are also backed up by our results for structural change in Table 8. That is, we find no qualitative change in cross market transmission of France yield shocks from the interdependence and the ECB announcement period. Clearly, these channels suggest that buying French bonds brings down yield levels of the complete EA core.

When inspecting the cross market transmissions of Italian shocks given in the fourth column of matrices $\boldsymbol{B}^{S*}$ in Table 6 we again find transmissions are qualitatively the same after the ECB announcement as compared to the interdependence sample. However, from parameter estimates in Table 6 as well as from the test results in Table 8 we infer a smaller instantaneous impact on German bond markets compared to interdependence. This effect is a survivor of the Euro crisis period and hence not a result of the ECB announcement.

The same holds true for the cross market transmission of Spanish shocks as can be inferred from the respective second columns of $\boldsymbol{B}^{S*}$. Firstly, compared to S_2, Spanish shocks continue to induce positive comovements in Italian bond yields. Secondly, a significant negative impact on German and France bond yields associated with capital flows induced by Spanish shocks survives the ECB announcement. That is, the latter two linkages were insignificant in interdependence times.[9] Interestingly, given the current yield levels of the core countries producing positive news for Spanish refinancing conditions leads to yield convergence of the complete EA core. That is, a focus of the ECB on buying Spanish bonds would lead to converging yield levels.[10]

For German bond market shocks we find another significant negative impact on France yields

[9]Formal tests in Table 8 show no difference in parameter estimates.

[10]To say something about convergence it is neccessary to take yield levels into account. To the end of our sample period Italian yields are the highest followed by Spanish, French and German yield levels. Moreover, since cross market transmissions of Spanish home market news are such that Italian yields develop in the same direction as Spanish yields, while German and French yields develop inversely buying Spanish bonds, e.g., in

in S_3, which is found insignificant in interdependence times.[11] That is, German shocks normalized to a unit impact now even lead to a negative impact of -0.928 on France yields, which is a nearly one to one negative transmission. That is, we see capital flows between the probably most stable economies France and Germany induced by shocks to the German bond market in the current period S_3. However, as can be inferred from the results in Table 6 the positive transmission from German shocks to Italy in the interdependence sample is not reestablished in S_3. The latter result is also backed up by the test results in Table 8.

From an instantaneous perspective we find mixed evidence for the effectiveness of the ECB announcement. On the one hand France provides an anchor for core EA yield pricing again, i.e. core yields tend to move in the same direction due to France yield shocks. Moreover, the impact of Italian shocks is qualitatively the same compared to the interdependence sample. On the other hand we find clear differences in cross market transmissions of German and Spanish shocks compared to S_1. Like in the case of Italian shocks we see mostly negative cross market transmissions from these countries to the rest of the EA core. Moreover, the positive linkage between Spain and Italy established in the Euro crisis is not removed after the ECB announcement. That is, southern EA member yields still develop in the same direction due to shocks on Spanish bond markets.

However, actual developments of EA government bond yields depend on the relative importance of these cross market transmission channels. On the one hand, negative transmissions produce inverse developments in yields and thus inversely develop refinancing conditions. On the other hand, positive cross market transmissions lead to positively related comovements in EA yield. The next section provides evidence on the relative importance of country specific shocks for other core EA countries refinancing conditions in the periods under investigation.

2.3.6 Changes in the relative importance of cross country transmissions

Table 9 summarizes h step ahead forecast error variance decompositions for core EA countries and periods S_1 to S_3. These display the relative importance of country specific unit shocks (in columns) for the variation of the considered EA yields.[12]

As can be inferred from the respective third columns of Table 9 structural shocks to France are the leading driver of EA yields in the interdependence sample S_1. That is, for $h \to \infty$ shocks to French yields explain approximately 51%, 62%, 95% and 75% of German, Spanish, French and Italian yield variation, respectively. Thus, prior to the Euro crisis which we assume to be triggered by distrust in Maastricht convergence markets used to price EA debt for Germany, Italy and Spain relative to French yield developments. However, we find that French yields indeed provide an important anchor for yield pricing in S_1.

Moreover, we find differences in the relative importance of home market news for yield pricing.

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the PSPP leads to convergence. Moreover, since cross market transmissions of Spanish news to French yields are economically insignificant yields approximately converge to currently observed French yield level.

[11] Formal tests for differences in parameters again suggest no difference in estimates between periods S_1 and S_3.

[12] That is, we stick to our ordering assumptions and use $\boldsymbol{B}$ to calculate decompositions. This way, we scale $\boldsymbol{B}^*$ with our structural variance estimates to obtain comparable effects of unit shocks. From a theoretical perspective this is in line with taking differences in intensities, i.e. differences in the rate of country specific news arrivals into account (c.f. Clark 1976, Tauchen and Pitts 1983 or Haas and Mueller 2016).

That is, for northern European countries, i.e. for Germany and France own shocks play an important role in debt pricing with 46% and 95%, respectively . However, for southern core members the picture is different. Spanish shocks account for only 18% of own yield variation, while for Italy we find home market shocks are an economically insignificant driver of own yield variation with only 5%. That is, in the interdependence sample results suggest markets price southern EA core yields mainly through developments in northern yield markets and thus neglect southern home market news.

This picture changes dramatically in the Euro crisis period S_2 after markets received a signal about Greece not fulfilling Maastricht criteria. In this period markets changed their pricing rules accordingly and we find own country specific shocks are now the main driver of yield developments for Germany, Spain and France, with 64%, 79% and 70%, respectively. That is, we find markets price core EA debt for these countries mainly through their respective home market news.

Clearly, this EA wide change to country specific debt pricing may be the result of general mistrust in the Euro. However, we find this is not true for Italy, which with 53% is now mainly driven by Spanish shocks. Moreover, Spanish shocks explain an economically significant share of German and France yield variation with 27% and 16%, too. That is, two major changes in pricing rules arise in the Euro crisis. Firstly, France loses its anchor function for EA debt pricing compared to S_1. Instead, we find market participants rely on country specific news. Secondly, Spanish home market shocks now explain an economically significant share of variation for all EA core yields in S_2. However, cross market transmissions of Spanish news in S_2 lead to positive comovements in Italy, while the same news lead to inverse yield developments in the northern core.

Yield pricing rules for the period after the ECB announcement S_3 are again depicted in Table 9. As we argue a credible announcement should reestablish interdependencies since any deviations from pre crisis pricing rules is going to be neutralized and thus punished by monetary authorities.

Indeed, we find some evidence for an effective ECB announcement to preserve the Euro. Firstly, when inspecting the third columns of Table 9 in S_3 we see shocks to French yields are again the relatively most important driver for German, France and Italian yield variation with 54%, 83% and 48%, respectively. However, for Spain own shocks remain the main driver with 62% as in S_2, but France shocks with 28% are the second important source of variation for Spain. Moreover, as established in the Euro crisis period home market shocks, i.e. country specific news remain an important driver after the ECB announcement for Germany, Spain and France with 36%, 62% and 83%, respectively. However, when taking trade intensities into account Spanish cross market transmissions to Germany and France are neglectable in S_1 and S_3, but not in during the Euro crisis S_2. Thus, the ECB announcement dampened the relative importance of Spanish shocks for these countries.

As also observed in interdependence times S_1 the case of Italy remains a special one. On the one hand like in interdependence times French shocks again provide an anchor for Italian yield pricing. On the other hand, Spanish home market news with 30% variation explained are relatively more important than Italian home market developments, which explain only

20% of Italian yield variation compared to 5% and 27% in S_1 and S_2, respectively.

2.3.7 Robustness check

As a first check we identified our system of equations in (2.1) by employing conditional heteroscedastictiy as, e.g., in Haas and Mueller (2016). That is, *ceteris paribus* we assumed u_t to follow a scale mixture of normals. One particular merit of this scheme is that observations are endogeneously assigned to different variance regimes. Thus, no arbitrary assumptions on the timing of changes from high to low variances are needed. Moreover, just like the estimator described in Section 2.2.3 the normal mixture estimator is consistent and asymptotically normal (c.f. Lanne and Lütkepohl 2010). However, in small samples parameter estimates may still differ. Indeed, our samples exhibit differences in length, i.e. the interdependence sample S_1 is 2037 observations long, the debt crisis sample S_2 has 589 observations and for the sample after the ECB announcement S_3 the number of observations is 994.
Again it is instructive to compare estimates free of scale, i.e. estimates $\hat{\boldsymbol{B}}^*$ for S_1 to S_3. In line with the arguments already provided in Section 2.2.2 variance states from a scale mixture may differ from unconditional variance states used for identification and thus may lead to differences in scaled parameters $\boldsymbol{B}$. Analogous to our baseline model in Section 2.2.2 we estimate a scale mixture of two normal distributions for u_t. Moreover, for our robustness check we rely on nummerically distinct shifts in structural variances like in Rigobon (2003). However, in doing so our ordering scheme fails for a mixture of two states in the ECB announcement sample. This is most probably the case, because shifts in structural variances and hence structural shocks are indistinguishable. To be still able to deliver a robustness check for S_3 we reestimated the last sample assuming a mixture of three variance states. It turns out the third state exhibits both a very low state probability and highest reduced form variances. Haas and Mueller 2016 argue this state can be characterised as an outlier state. Hence, we use the other two states for identification.
Table IA.I in the internet appendix is similar to Table 6 and provides estimates $\hat{\boldsymbol{B}}^{S*}$ for samples S_1 to S_3 again normalized to a unit impact of a positive shock with standard errors in parentheses. Comparing results in both tables, one finds that cross market transmissions are qualitatively the same for all three subsamples, i.e. signs of significant transmission channels do not change with different statistical identification schemes even in small samples, e.g., like sample S_2. Moreover, as expected from two consistent estimators parameter estimates in the largest sample, i.e. S_1 are nummerically close together too, while in the smallest sample S_2 we find differences. However, differences in parameter estimates across identification schemes in the medium length sample S_3 may additionally stem from filtering outliers for the sake of identification.
Figure IA.I to Figure IA.III present normal mixture implied ex post probabilities of u_t for the high variance state as used for identification in S_1 to S_3. These figures also include breakpoints T_B employed for identification through unconditional heteroscedasticity. As is expected, scale mixture states show little persistence in contrast to our chosen unconditional

variance regimes. Nevertheless, Figure IA.I for S_1 and Figure IA.II for S_2 display changes in the state probability pattern around the formerly used breakpoints, while this is not as distinctly visible for S_3 in Figure IA.III. That is, we find differences in regime assignments of reduced form VAR residuals across statistical identification schemes. Nevertheless, estimates of cross market transmissions appear qualitatively and quantitatively robust to the choice of the statistical identification scheme in large samples, while in small samples we find cross market transmissions are at least qualitatively stable.

2.4 Conclusions

We find mixed evidence on the effectiveness of the ECB announcement to preserve the Euro in both reestablishing the interdependence pattern of linkages as well as their relative importance for EA long term refinancing conditions. Firstly, French bond market news provide an important anchor for core EA yield pricing in the current period in line with the results in interdependence times. Secondly, financial market participants do not rely on this anchor alone. That is, in contrast to the interdependence sample country specific news are another important pricing factor for the core EA bond yields under investigation. That is, compared to pre crisis times we find economic proximity is priced on a less granular level since the beginning of the crisis as well as in the current period after the ECB announcement. As we argue this persistent change in market participants behavior is in line with a loss of credibility in the Euro as a common currency, since markets do not believe in economic convergence. That is, the ECB announcement was not fully effective in neutralizing the effects thereof. Thirdly, the Italian bond market remains a special case. We find that shift contagion linkages established between Spain and Italy in the Euro crisis period remain active after the ECB announcement.

Until March 31st 2017 the ECB bought government bonds in their public sector purchase program (PSPP) in amount of 1.48 trillion Euro in book value.[13] Moreover, the current ECB strategy rests on bond purchases in line with the relative capital subscriptions of EA members.[14] Apart from the question if the ECB should buy government debt at all, our diagnosed pattern of cross market transmissions may guide policy makers to an optimal buying strategy with regard to lower yield levels as well as yield convergence. For example, as our results suggest, buying French bonds has an indirect stabilizing effect, i.e. brings down yield levels of the complete EA core. Moreover, given currently observed yield levels buying Spanish bonds leads to convergence of core EA country long term refinancing conditions.

[13] c.f., https://www.ecb.europa.eu/mopo/implement/omt/html/index.en.html

[14] For ECB capital subscriptions see, https://www.ecb.europa.eu/ecb/orga/capital/html/index.en.html

2.5 References

Ang, A. and M. Piazzesi, 2003. "A no-arbitrage vector autoregression of term structure dynamics with macroeconomic and latent variables", *Journal of Monetary Economics*, 50, 745-787.

Blanchard, O. J. and D. Quah, 1989. "The Dynamic Effects of Aggregate Demand and Supply Disturbances". *The American Economic Review*, 79, 655-673.

Candelon, B. and H. Lütkepohl, 2001. "On the Reliability of Chow-type Tests for Parameter Constancy in Multivariate Dynamic Models", *Economics Letters*, 73, 155-160.

Clark, P. K., 1973, A subordinated stochastic process model with finite variance for speculative prices, *Econometrica*, 41, 135-155.

De Grauwe, P., and Y. Ji, 2013. "Self-Fulfilling Crises in the Eurozone: An Empirical Test", *Journal of International Money and Finance*, 34, 15-36.

Faust, J., 1998. "The Robustness of Identified VAR Conclusions about Money", *Carnegie-Rochester Conference Series on Public Policy*, 49, 207-244.

Forbes, K. J. and R. Rigobon, 2002. "No Contagion, Only Interdependence: Measuring Stock Market Comovements", *Journal of Finance*, 57, 2223-2261.

Fry, R. and A. Pagan, 2007. "Some Issues using Sign Restrictions for Identifying Structural VARs", *Working Paper*; National Center of Econometric Research.

Greene, W. H., 2003, "Eonometric Analysis", New Jersey: Pearson.

Golub, G. H. and C. F. Loan, 1989. "Matrix Computations", Baltimore: The Johns Hopkins University Press.

Haas, M. and S. Mueller, 2016. "FX pricing and strategic trading", Working Paper.

Lanne, M. and H. Lütkepohl, 2006. "Identifying Monetary Policy Shocks via Changes in Volatility", *CES IFO Working Paper*, 1744, 1-26.

Lanne, M. and H. Lütkepohl, 2008. "Identifying Monetary Policy Shocks via Changes in Volatility", *Journal of Money, Credit and Banking*, 40, 1131-1149.

Lütkepohl, H., 1996. "Handbook of Matrices", New York: Wiley and Sons.

Rigobon, R., 2003. "Identification through Heteroscedasticity", *The Review of Economics and Statistics*, 84, 777-792.

Tauchen, G. E. and M. Pitts, 1983, "The Price Variability-Volume Relationship on Speculative Markets", *Econometrica*, 51, 485-505.

Forbes, K. and R. Rigobon, 2001. "Measuring contagion: conceptual and empirical issues." International financial contagion. Springer US, 43-66.

Uhlig, H., 2005. "What are the Effects of Monetary Policy on Output? Results from an Agnostic Identification Procedure", *Journal of Monetary Economics*, 52, 381-419.

Zellner, A., 1962. "An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias". *Journal of the American Statistical Association*; 57 (298); 348-368.

2.6 Appendix

Appendix A: Figures

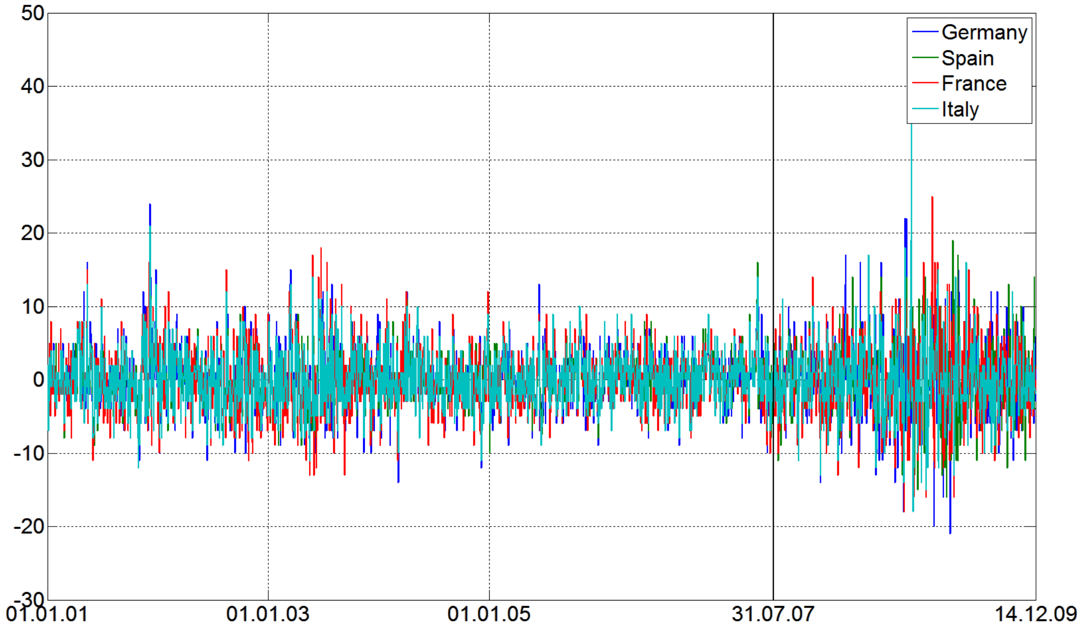

FIGURE 2: First differences of long-term goverment bond yields p.a. with ten years to maturity for core EA countries Germany (dark blue), Spain (green), France (red) and Italy (light blue) corresponding to the interdependence sample (S_1: 01/01/2001 to 14/12/2009). The bold horizontal line displays the change in unconditional variance (T_B: 31/07/2007) used for structural identification. Daily yields are drawn from the EUROSTAT Maastricht convergence series.

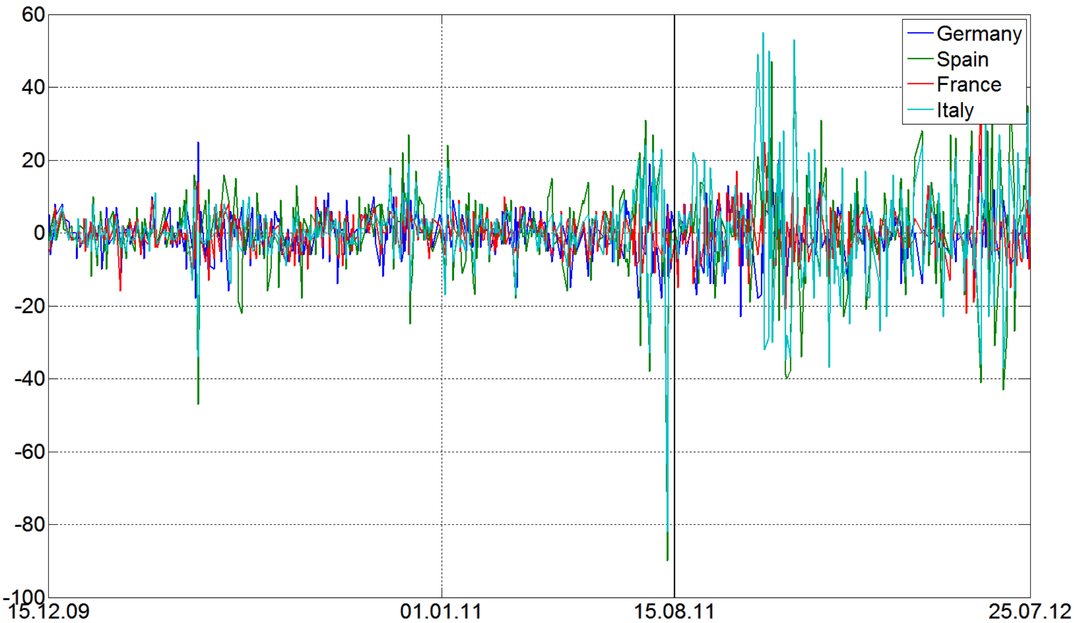

FIGURE 3: First differences of long-term goverment bond yields p.a. with ten years to maturity for core EA countries Germany (dark blue), Spain (green), France (red) and Italy (light blue) corresponding to the debt crisis sample (S_2: 15/12/2009 to 25/07/2012). The bold horizontal line displays the change in unconditional variance (T_B: 15/08/2011) used for structural identification. Daily yields are drawn from the EUROSTAT Maastricht convergence series.

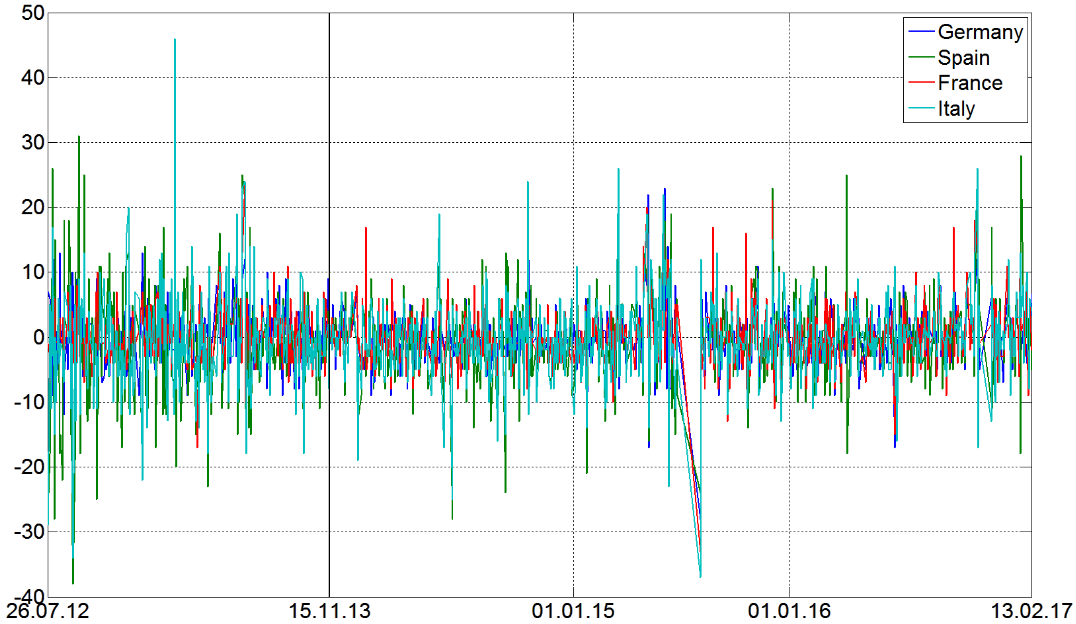

FIGURE 4: First differences of long-term goverment bond yields p.a. with ten years to maturity for core EA countries Germany (dark blue), Spain (green), France (red) and Italy (light blue) corresponding to the ECB announcement sample (S_3: 26/07/2012 to 13/02/2017). The bold horizontal line displays the change in unconditional variance (T_B: 15/11/2013) used for structural identification. Daily yields are drawn from the EUROSTAT Maastricht convergence series. Missing data for 07/2015 is due to unavailability of Greek yield data in this month.

Appendix B: Tables

Table 1a

Current ECB purchases under the public sector purchase program (PSPP) and paid-up capital of EA member national central banks

EA member	**Cumulative purchase**(a)	**relative purchase**(b)	**paid-up capital**(c)	**capital key**(d)
Germany	355,594.000	26.958	1,948.209	25.567
France	282,373.000	21.407	1,534.899	20.143
Italy	245,582.000	18.618	1,332.645	17.489
Spain	175,947.000	13.339	957.028	12.560
Netherlands	79,540.000	6.030	433.379	5.687
Belgium	49,092.000	3.722	268.222	3.520
Greece	0.000	0.000	220.094	2.888
Austria	39,014.000	2.958	212.506	2.789
Portugal	26,617.000	2.018	188.723	2.477
Finland	23,526.000	1.784	136.005	1.785
Ireland	20,231.000	1.534	125.646	1.649
Slovakia	9,084.000	0.689	83.623	1.097
Lithuania	2,473.000	0.187	44.729	0.587
Slovenia	5,397.000	0.409	37.400	0.491
Latvia	1,474.000	0.112	30.537	0.401
Luxembourg	1,893.000	0.144	21.975	0.288
Estonia	65.000	0.005	20.871	0.274
Cyprus	248.000	0.019	16.378	0.215
Malta	915.000	0.069	7.015	0.092
Supranationals	162,150.000	–	–	–
$\boldsymbol{\Sigma}$	1,481,216.000	100.00	7,619.885	100.00

Table 1a: Absolute and relative ECB purchases of government bonds under the public sector purchase program (PSPP) and paid-up capital of EA member national central banks. a: cumulative purchases until 31th of March in million Euro (book value). Figures are obtained from https://www.ecb.europa.eu/mopo/implement/omt/html/index.en.html. b: relative purchase in % (excluding supranationals). c: in million Euro. Figures are obtained from https://www.ecb.europa.eu/ecb/orga/capital/html/index.en.html d: capital key in % (EA members only).

Table 1

Principal component estimates of periphery yields for periods $S_1, ..., S_3$

	S_1		S_2		S_3	
Country	$\boldsymbol{PC_2}$	$\boldsymbol{PC_1}$	$\boldsymbol{PC_2}$	$\boldsymbol{PC_1}$	$\boldsymbol{PC_2}$	$\boldsymbol{PC_1}$
Austria	0.1	13.3	0.0	0.0	2.4	0.0
Belgium	2.3	12.4	0.2	0.0	1.7	0.0
Greece	2.9	14.5	0.4	99.6	1.2	98.6
Finland	1.6	13.8	0.1	0.0	0.9	0.0
Ireland	8.2	16.2	20.3	0.1	10.6	0.3
Luxembourg	84.0	7.2	0.1	0.0	1.1	0.0
Netherlands	0.8	11.9	0.1	0.0	2.1	0.0
Portugal	0.2	10.7	0.789	0.2	80.0	1.1
CV	16.5	53.0	10.3	83.6	10.2	79.2

Table 1: Estimates of country-wise Loadings and normalized Eigenvalues for $j = 1, 2$ first and second principal component (PC_j) of periphery yields. Loadings display the percent variation of country i explained by principal component $j = 1, 2$. Normalized Eigenvalues show the percentage of the common periphery yield variation (CV) explained by prinicipal component j.

Table 2a

Reduced form VAR estimates for period S_1 with standard errors (in parentheses).

Parameters significant at a 5% level in bold.

Parameter	**Germany**	**Spain**	**France**	**Italy**
ν	-0.047 (0.073)	-0.046 (0.069)	-0.066 (0.092)	-0.044 (0.073)
$Germany_{t-1}$	**-0.480** (0.038)	**-0.165** (0.038)	-0.087 (0.046)	**-0.273** (0.039)
$Spain_{t-1}$	0.039 (0.042)	**-0.391** (0.042)	0.060 (0.050)	-0.075 (0.043)
$France_{t-1}$	**0.418** (0.034)	**0.255** (0.033)	**-0.332** (0.042)	**0.202** (0.035)
$Italy_{t-1}$	**-0.103** (0.045)	**0.120** (0.045)	0.070 (0.053)	-0.057 (0.046)
$Germany_{t-2}$	**-0.217** (0.035)	**-0.097** (0.035)	-0.039 (0.042)	**-0.144** (0.036)
$Spain_{t-2}$	0.053 (0.041)	**-0.111** (0.041)	-0.029 (0.049)	-0.010 (0.042)
$France_{t-2}$	**0.270** (0.029)	**0.173** (0.028)	**-0.077** (0.036)	**0.174** (0.029)
$Italy_{t-2}$	0.016 (0.042)	**0.127** (0.042)	0.081 (0.049)	0.032 (0.043)
$PC_{2,t-1}$	**0.034** (0.014)	0.016 (0.014)	-0.001 (0.017)	0.014 (0.014)
$PC_{1,t-1}$	**0.059** (0.021)	**0.081** (0.021)	**0.066** (0.026)	**0.065** (0.021)
US_{t-1}	**0.267** (0.014)	**0.228** (0.013)	**0.204** (0.017)	**0.247** (0.014)
R^2	0.417	0.321	0.088	0.264
$\bar{R}^2$	0.417	0.320	0.087	0.263

Table 2a: Reduced form VAR (2) estimates for period S_1 with standard errors (in parentheses). Period S_1 is the interdependence sample running from 01/01/2001 until 14/12/2009. $y_t = (Germany_t, Spain_t, France_t, Italy_t)'$ are ten year to maturity government bond yields in first differences at time t for Germany, Spain, France and Italy, respectively. $PC_{j,t}$ are principal components $j = 1, 2$ of periphery yields of the EA 12 not included in y_t and as reported in Table 1. US_t is the U.S. ten year to maturity governement bond yield in first differences at time t. ν is a constant. Parameters significant at a 5% level are given in bold.

Table 2b

Reduced form VAR estimates for period S_2 with standard errors (in parentheses).

Parameters significant at a 5% level in bold.

Parameter	**Germany**	**Spain**	**France**	**Italy**
ν	−0.145 (0.195)	0.468 (0.428)	−0.159 (0.204)	0.301 (0.357)
$Germany_{t-1}$	**-0.325** (0.043)	**0.350** (0.095)	−0.058 (0.046)	**0.269** (0.082)
$Spain_{t-1}$	−0.009 (0.030)	**0.244** (0.068)	0.025 (0.034)	0.042 (0.062)
$France_{t-1}$	**0.283** (0.043)	0.134 (0.096)	−0.039 (0.048)	0.047 (0.086)
$Italy_{t-1}$	−0.003 (0.033)	−0.077 (0.075)	−0.012 (0.038)	0.050 (0.071)
$Germany_{t-2}$	0.034 (0.040)	0.015 (0.089)	−0.002 (0.043)	0.063 (0.076)
$Spain_{t-2}$	0.026 (0.029)	−0.014 (0.066)	0.044 (0.033)	0.022 (0.061)
$France_{t-2}$	**0.145** (0.045)	−0.006 (0.100)	0.059 (0.050)	−0.101 (0.090)
$Italy_{t-2}$	−0.032 (0.033)	−0.047 (0.074)	−0.028 (0.038)	−0.035 (0.070)
$PC_{2,t-1}$	0.004 (0.009)	**0.041** (0.019)	0.005 (0.009)	**0.040** (0.017)
$PC_{1,t-1}$	0.003 (0.003)	−0.005 (0.008)	−0.004 (0.004)	−0.002 (0.008)
US_{t-1}	**0.417** (0.032)	**-0.173** (0.070)	**0.126** (0.033)	**-0.114** (0.059)
R^2	0.308	0.077	0.014	0.021
$\bar{R}^2$	0.305	0.072	0.008	0.016

Table 2b: Reduced form VAR (2) estimates for period S_2 with standard errors (in parentheses). Period S_2 is the Euro crisis sample from 15/12/2009 to 25/07/2012. $y_t = (Germany_t, Spain_t, France_t, Italy_t)'$ are ten year to maturity government bond yields in first differences at time t for Germany, Spain, France and Italy, respectively. $PC_{j,t}$ are principal components $j = 1, 2$ of periphery yields of the EA 12 not included in y_t and as reported in Table 1. US_t is the U.S. ten year to maturity governement bond yield in first differences at time t. ν is a constant. Parameters significant at a 5% level are given in bold.

Table 2c

Reduced form VAR estimates for period S_3 with standard errors (in parentheses).

Parameters significant at a 5% level in bold.

Parameter	**Germany**	**Spain**	**France**	**Italy**
ν	-0.129 (0.110)	**-0.499** (0.203)	-0.120 (0.137)	-0.347 (0.186)
$Germany_{t-1}$	**-0.364** (0.036)	**-0.235** (0.068)	0.043 (0.044)	**-0.196** (0.062)
$Spain_{t-1}$	-0.012 (0.023)	**-0.167** (0.047)	0.035 (0.028)	0.070 (0.042)
$France_{t-1}$	**0.329** (0.037)	**0.213** (0.070)	-0.168 (0.045)	**0.190** (0.064)
$Italy_{t-1}$	-0.001 (0.028)	0.070 (0.057)	0.017 (0.034)	**-0.155** (0.051)
$Germany_{t-2}$	**-0.105** (0.032)	-0.071 (0.059)	0.051 (0.039)	0.034 (0.054)
$Spain_{t-2}$	-0.021 (0.023)	-0.012 (0.046)	0.030 (0.027)	0.054 (0.041)
$France_{t-2}$	**0.172** (0.035)	0.109 (0.065)	**-0.091** (0.043)	0.079 (0.059)
$Italy_{t-2}$	-0.002 (0.027)	-0.075 (0.054)	-0.047 (0.032)	**-0.160** (0.048)
$PC_{2,t-1}$	-0.004 (0.012)	**-0.127** (0.027)	-0.016 (0.015)	**-0.114** (0.023)
$PC_{1,t-1}$	-0.006 (0.004)	-0.012 (0.008)	-0.002 (0.005)	-0.010 (0.007)
US_{t-1}	**0.303** (0.027)	-0.011 (0.050)	**0.189** (0.033)	0.016 (0.046)
R^2	0.307	0.057	0.043	0.075
$\bar{R}^2$	0.305	0.054	0.040	0.072

Table 2c: Reduced form VAR (2) estimates for period S_3 with standard errors (in parentheses). S_3 is the period after the ECB announcement from 26/07/2012 to 22/02/2017. $y_t = (Germany_t, Spain_t, France_t, Italy_t)'$ are ten year to maturity government bond yields in first differences at time t for Germany, Spain, France and Italy, respectively. $PC_{j,t}$ are principal components $j = 1, 2$ of periphery yields of the EA 12 not included in y_t and as reported in Table 1. US_t is the U.S. ten year to maturity governement bond yield in first differences at time t. ν is a constant. Parameters significant at a 5% level are given in bold.

Table 3

Likelihood ratio test results for no (within period) change

in reduced form covariances ($H_0 : \Sigma_{u1} = \Sigma_{u2}$) for periods $S_1, ..., S_3$.

Period	**break:** T_B	**test statistic**	**p-value**
S_1	31/07/2007	11397.636	0.000
S_2	15/08/2011	2615.129	0.000
S_3	15/11/2013	3495.942	0.000

Table 3: Likelihood ratio test results for no (within period) change in reduced form covariances ($H_0 : \Sigma_{u1} = \Sigma_{u2}$) for periods $S_1, ..., S_3$. Period S_1 is the interdependence sample running from 01/01/2001 until 14/12/2009. Period S_2 is the Euro crisis sample from 15/12/2009 to 25/07/2012. S_3 is the period after the ECB announcement from 26/07/2012 to 22/02/2017. T_B is the assumed breakpoint, i.e. the first observation of the second volatility regime. The value of the test statistic for the likelihood ratio test is reported as test statistic in column three and p-value is the corresponding p-value of the test in column five.

Table 4

Structural variance estimates $\Omega = diag(\omega_i)$ for periods $S_1, ..., S_3$,

where Std.-error is the corresponding standard error.

	S_1		S_2		S_3	
Parameter	**Estimate**	**Std.-error**	**Estimate**	**Std.-error**	**Estimate**	**Std.-error**
ω_1	2.323	0.166	1.566	0.191	0.879	0.086
ω_2	8.368	0.597	2.287	0.278	0.293	0.029
ω_3	1.617	0.115	3.829	0.466	1.613	0.157
ω_4	13.316	0.950	8.957	1.090	0.421	0.041

Table 4: Structural variance estimates $\Omega = diag(\omega_i)$ for periods $S_1, ..., S_3$. Period S_1 is the interdependence sample running from 01/01/2001 until 14/12/2009. Period S_2 is the Euro crisis sample from 15/12/2009 to 25/07/2012. S_3 is the period after the ECB announcement from 26/07/2012 to 22/02/2017. Std.-error is the corresponding standard error.

Table 5

Wald tests for equality of ω_i from Table 4 for periods $S_1, ..., S_3$,

where test stat. is the value of the test statistic.

	S_1		S_2		S_3	
H_0 :	**test stat.**	**p-value**	**test stat.**	**p-value**	**test stat.**	**p-value**
$\omega_1 = \omega_2$	149.596	0.000	44.602	0.000	16.855	0.000
$\omega_1 = \omega_3$	130.087	0.000	35.147	0.000	68.458	0.000
$\omega_1 = \omega_4$	19.466	0.000	18.715	0.000	54.019	0.000
$\omega_2 = \omega_3$	12.224	0.000	4.564	0.033	42.254	0.000
$\omega_2 = \omega_4$	123.396	0.000	20.192	0.000	23.364	0.000
$\omega_3 = \omega_4$	95.304	0.000	8.066	0.005	6.559	0.010

Table 5: Wald tests for equality of ω_i from Table 4 for periods $S_1, ..., S_3$, where test stat. is the value of the test statistic and p-value is the corresponding p-value of the test. Period S_1 is the interdependence sample running from 01/01/2001 until 14/12/2009. Period S_2 is the Euro crisis sample from 15/12/2009 to 25/07/2012. S_3 is the period after the ECB announcement from 26/07/2012 to 22/02/2017.

Table 6
Estimates $\hat{\boldsymbol{B}}^{S*}$ for $(Germany_t, Spain_t, France_t, Italy_t)'$ and periods $S_1, ..., S_3$ corresponding to the ordering of the ω_i in Table 4 with Standard errors (in parentheses). Parameters significant at a 5% level in bold.

$$\hat{\boldsymbol{B}}^{1*} = \begin{bmatrix} 1.000 & \underset{(0.096)}{-0.148} & \underset{(0.089)}{\mathbf{0.613}} & \underset{(0.134)}{\mathbf{-0.726}} \\ \underset{(0.078)}{\mathbf{0.568}} & 1.000 & \underset{(0.059)}{\mathbf{0.604}} & \underset{(0.187)}{-0.214} \\ \underset{(0.349)}{-0.428} & \underset{(0.085)}{0.014} & 1.000 & \underset{(0.116)}{\mathbf{-0.340}} \\ \underset{(0.096)}{\mathbf{0.610}} & \underset{(0.094)}{0.088} & \underset{(0.065)}{\mathbf{0.711}} & 1.000 \end{bmatrix}$$

$$\hat{\boldsymbol{B}}^{2*} = \begin{bmatrix} 1.000 & \underset{(0.108)}{\mathbf{-0.274}} & \underset{(0.137)}{-0.108} & \underset{(0.041)}{\mathbf{-0.172}} \\ \underset{(0.717)}{0.783} & 1.000 & \underset{(0.409)}{0.709} & \underset{(0.118)}{0.079} \\ \underset{(0.132)}{\mathbf{0.448}} & \underset{(0.105)}{-0.199} & 1.000 & \underset{(0.084)}{0.038} \\ \underset{(0.504)}{0.702} & \underset{(0.041)}{\mathbf{0.647}} & \underset{(0.299)}{0.520} & 1.000 \end{bmatrix}$$

$$\hat{\boldsymbol{B}}^{3*} = \begin{bmatrix} 1.000 & \underset{(0.046)}{\mathbf{-0.217}} & \underset{(0.088)}{\mathbf{0.645}} & \underset{(0.093)}{\mathbf{-0.237}} \\ \underset{(0.246)}{0.421} & 1.000 & \underset{(0.091)}{\mathbf{0.748}} & \underset{(0.533)}{-0.544} \\ \underset{(0.388)}{\mathbf{-0.928}} & \underset{(0.044)}{\mathbf{-0.097}} & 1.000 & \underset{(0.107)}{\mathbf{-0.230}} \\ \underset{(0.280)}{0.097} & \underset{(0.128)}{\mathbf{0.658}} & \underset{(0.083)}{\mathbf{0.918}} & 1.000 \end{bmatrix}$$

Table 6: Estimates $\hat{\boldsymbol{B}}^{S*}$ for $(Germany_t, Spain_t, France_t, Italy_t)'$ and periods $S_1, ..., S_3$ corresponding to the ordering of the ω_i in Table 4 with standard errors (in parentheses). Period S_1 is the interdependence sample running from 01/01/2001 until 14/12/2009. Period S_2 is the Euro crisis sample from 15/12/2009 to 25/07/2012. S_3 is the period after the ECB announcement from 26/07/2012 to 22/02/2017. Parameters significant at a 5% level are given in bold.

Table 7

Tests for no structural change of parameter estimates from Table 6, where
$H_0 : \hat{\boldsymbol{B}}_{ij}^{1*} = \hat{\boldsymbol{B}}_{ij}^{2*}$ for $i \neq j$ and $i, j = 1, ..., 4$.
The table presents test statistics with p-values (in parentheses).

$$\begin{bmatrix} 1.000 & \underset{(0.382)}{0.763} & \underset{(0.000)}{19.493} & \underset{(0.000)}{15.659} \\ \underset{(0.765)}{0.089} & 1.000 & \underset{(0.799)}{0.065} & \underset{(0.185)}{1.758} \\ \underset{(0.019)}{5.522} & \underset{(0.115)}{2.487} & 1.000 & \underset{(0.008)}{6.949} \\ \underset{(0.858)}{0.032} & \underset{(0.000)}{29.729} & \underset{(0.532)}{0.390} & 1.000 \end{bmatrix}$$

Table 7: Wald test results for no structural change of parameter estimates for the interdependence period S_1 versus the Euro crisis period S_2 from Table 6, where $H_0 : \hat{\boldsymbol{B}}_{ij}^{1*} = \hat{\boldsymbol{B}}_{ij}^{2*}$ for $i \neq j$ and $i, j = 1, ..., 4$. Period S_1 is the interdependence sample running from 01/01/2001 until 14/12/2009. Period S_2 is the Euro crisis sample from 15/12/2009 to 25/07/2012. The table presents test statistics together with corresponding p-values (in parentheses).

Table 8

Tests for no structural change of parameter estimates from Table 6, where
$H_0 : \hat{\boldsymbol{B}}_{ij}^{1*} = \hat{\boldsymbol{B}}_{ij}^{3*}$ for $i \neq j$ and $i, j = 1, ..., 4$.
The table presents test statistics with p-values (in parentheses).

$$\begin{bmatrix} 1.000 & \underset{(0.512)}{0.429} & \underset{(0.797)}{0.066} & \underset{(0.003)}{9.033} \\ \underset{(0.571)}{0.321} & 1.000 & \underset{(0.184)}{1.762} & \underset{(0.559)}{0.341} \\ \underset{(0.338)}{0.919} & \underset{(0.248)}{1.336} & 1.000 & \underset{(0.484)}{0.489} \\ \underset{(0.083)}{3.014} & \underset{(0.000)}{12.877} & \underset{(0.049)}{3.872} & 1.000 \end{bmatrix}$$

Table 8: Wald test results for no structural change of parameter estimates for the interdependence period S_1 versus the ECB announcement period S_3 from Table 6, where $H_0 : \hat{\boldsymbol{B}}_{ij}^{1*} = \hat{\boldsymbol{B}}_{ij}^{3*}$ for $i \neq j$ and $i, j = 1, ..., 4$. Period S_1 is the interdependence sample running from 01/01/2001 until 14/12/2009. S_3 is the period after the ECB announcement from 26/07/2012 to 22/02/2017. The table presents test statistics together with corresponding p-values (in parentheses).

Table 9

$\boldsymbol{h}$–step ahead forecast error variance decompositions for $\boldsymbol{y}_t = (Germany_t, Spain_t, France_t, Italy_t)'$ in rows and % variation explained by news from countries in $\boldsymbol{y}_t$ in periods $S_1, ..., S_3$ in columns.

		S_1				S_2				S_3			
Country	$\boldsymbol{h}$	**Germany**	**Spain**	**France**	**Italy**	**Germany**	**Spain**	**France**	**Italy**	**Germany**	**Spain**	**France**	**Italy**
Germany	1	36.840	0.329	59.805	3.026	67.577	29.139	0.824	2.461	27.972	8.523	60.764	2.741
	2	46.049	0.419	50.948	2.584	63.919	26.592	6.960	2.530	35.692	7.665	54.228	2.416
	3	46.221	0.461	50.680	2.638	63.995	26.422	6.912	2.671	35.696	7.668	54.223	2.413
	4	45.730	0.539	51.131	2.599	63.906	26.517	6.910	2.667	35.778	7.622	54.195	2.406
	5	45.601	0.542	51.270	2.587	63.909	26.509	6.911	2.672	35.820	7.617	54.160	2.403
	∞	45.591	0.546	51.278	2.586	63.909	26.509	6.910	2.672	35.819	7.616	54.160	2.404
Spain	1	13.924	17.642	68.127	0.308	8.904	83.305	7.679	0.112	1.765	64.027	29.066	5.142
	2	19.648	17.979	61.753	0.620	12.534	79.129	8.018	0.319	4.069	62.392	28.096	5.443
	3	19.923	17.867	61.502	0.708	12.501	78.940	8.186	0.372	4.104	62.149	28.109	5.639
	4	19.754	17.695	61.847	0.704	12.504	78.896	8.213	0.388	4.199	62.065	28.104	5.633
	5	19.736	17.639	61.923	0.702	12.504	78.893	8.215	0.388	4.238	62.028	28.100	5.634
	∞	19.738	17.634	61.926	0.702	12.505	78.892	8.215	0.388	4.240	62.026	28.100	5.634
France	1	4.046	0.002	95.555	0.397	13.559	15.373	70.950	0.117	13.804	0.975	83.741	1.480
	2	4.060	0.047	95.357	0.536	13.702	15.893	70.289	0.116	14.279	1.246	83.002	1.473
	3	4.058	0.093	95.297	0.553	13.882	15.855	70.083	0.180	14.265	1.259	82.925	1.551
	4	4.057	0.097	95.287	0.559	13.879	15.868	70.072	0.180	14.297	1.261	82.886	1.555
	5	4.057	0.097	95.287	0.559	13.881	15.868	70.070	0.182	14.298	1.263	82.882	1.557
	∞	4.057	0.097	95.287	0.559	13.881	15.868	70.069	0.182	14.298	1.263	82.881	1.557
Italy	1	13.709	0.116	80.445	5.730	11.185	54.547	6.459	27.809	0.104	31.142	49.206	19.548
	2	19.290	0.127	75.211	5.372	13.678	52.942	6.392	26.988	1.493	30.483	48.199	19.825
	3	19.400	0.140	75.072	5.387	13.671	52.931	6.393	27.005	1.756	30.426	47.676	20.142
	4	19.374	0.158	75.128	5.341	13.684	52.898	6.426	26.993	1.755	30.411	47.656	20.177
	5	19.395	0.158	75.122	5.325	13.685	52.897	6.427	26.992	1.774	30.401	47.650	20.175
	∞	19.397	0.160	75.119	5.324	13.685	52.896	6.427	26.992	1.778	30.399	47.648	20.174

Table 9: $\boldsymbol{h}$–trading days ahead forecast error variance decompositions for $\boldsymbol{y}_t = (Germany_t, Spain_t, France_t, Italy_t)'$ in rows and % variation explained by news from countries in $\boldsymbol{y}_t$ in periods S_1 in columns 3-6 in S_2 in columns 7-10 and S_3 in columns 11-14 reported for the low variance regime. $y_t = (Germany_t, Spain_t, France_t, Italy_t)'$ are ten year to maturity governement bond yields in first differences at time t for Germany, Spain, France and Italy, respectively. Period S_1 is the interdependence sample running from 01/01/2001 until 14/12/2009. Period S_2 is the Euro crisis sample from 15/12/2009 to 25/07/2012. S_3 is the period after the ECB announcement from 26/07/2012 to 22/02/2017.

Appendix C: Simultaneous decomposition of two reduced form covariance matrices

Suppose Σ_i for $i = 1,2$ are two symmetric $(K \times K)$ positive-definite matrices. The following algorithm decomposes these matrices in $\Sigma_1 = \boldsymbol{B} I_K \boldsymbol{B}'$ and in $\Sigma_2 = \boldsymbol{B}\Omega\boldsymbol{B}'$, where I_K is an identity matrix of dimension K and $\Omega = diag(\omega_1, ..., \omega_K)$. Observationally equivalent we can decompose Σ_i for $i = 1,2$ in $\Sigma_1 = \boldsymbol{B}^*\Lambda_1\boldsymbol{B}^{*'}$ and $\Sigma_2 = \boldsymbol{B}^*\Lambda_2\boldsymbol{B}^{*'}$ with $\Lambda_i = diag(\lambda_{i1}, ..., \lambda_{iK})$, where $\boldsymbol{B}$, $\boldsymbol{B}^*$ are non singular matrices:

1) Derive a Cholesky decomposition $\Sigma_1 = GG'$, where G is a lower triangular matrix

2) Derive $C = G^{-1}\Sigma_2 G'^{-1}$

3) Derive Ω from a Schur decomposition of C, such that $Q'CQ = diag(\omega_1, ..., \omega_K) = \Omega$

4) Derive $\boldsymbol{B} = GQ'^{-1}$

5a) Assume a unique ordering of columns (and column signs) in $\boldsymbol{B}$ and corresponding $\Omega = diag(\omega_1, ..., \omega_K)$

5b) Derive $\boldsymbol{B}^* = \boldsymbol{B} diag(b_{11}, ..., b_{KK})^{-1}$

6) Derive structural variances $\Lambda_i = \boldsymbol{B}^{*-1}\Sigma_i\boldsymbol{B}^{*'-1}$ for $i = 1,2$.

As a result one obtains instantantaneous responses in $\boldsymbol{B}$ scaled to a unit shock in variance regime $i = 1$ and corresponding shifts in structural variances summarized in $\Omega = \Lambda_2\Lambda_1^{-1}$. Observationally equivalent one obtains responses $\boldsymbol{B}^*$ free of scale, i.e. responses normalized to a unit impact and structural variances summarized in $\Lambda_i = \boldsymbol{B}^{*-1}\Sigma_i\boldsymbol{B}^{*'-1}$ for variance regime $i = 1,2$ (for steps $1-4$ see also Golub and van Loan 1989).

2.7 Internet Appendix

Internet Appendix
On Interdependence and Shift Contagion between Core Euro Area Refinancing Conditions

This internet appendix provides additional results and robustness checks.

Additional figures and tables from statistical identification through a scale normal mixture

- Figure IA.I: Normal mixture implied ex post probabilities for the high conditional variance regime used for identification in the interdependence sample (S_1: 01/01/2001 to 14/12/2009)
- Figure IA.II: Normal mixture implied ex post probabilities (dark blue) for the high conditional variance regime used for identification in the debt crisis sample (S_2: 15/12/2009 to 25/07/2012)
- Figure IA.III: Normal mixture implied ex post probabilities (dark blue) for the high conditional variance regime used for identification in the ECB announcement sample (S_3: 26/07/2012 to 13/02/2017)
- Table IA.I: Normal mixture implied estimates $\boldsymbol{B}^*$ for periods S_1 to S_3

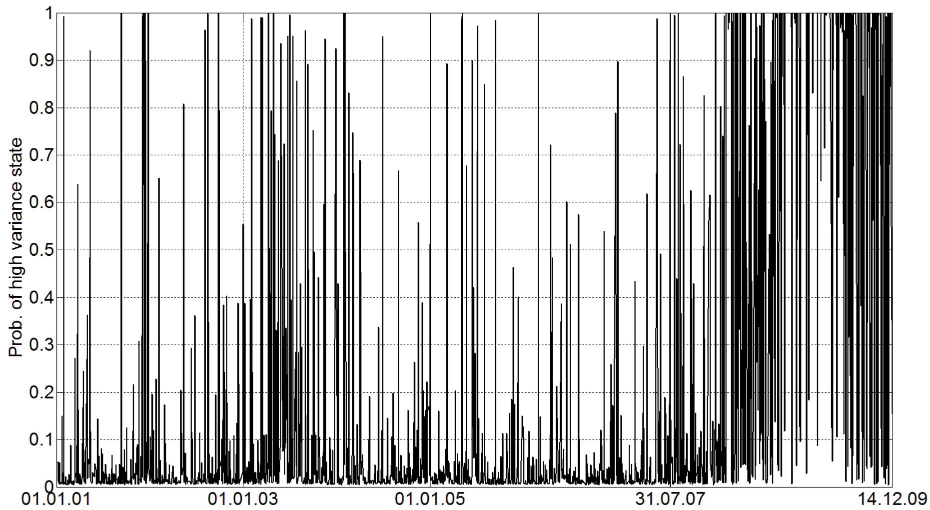

Figure IA.I: Normal mixture implied ex post probabilities (black) for the high conditional variance regime used for identification in the interdependence sample (S_1: 01/01/2001 to 14/12/2009). The bold horizontal line displays the assumed change in unconditional variance (T_B: 31/07/2007) used for identification as described in Section 2.3.

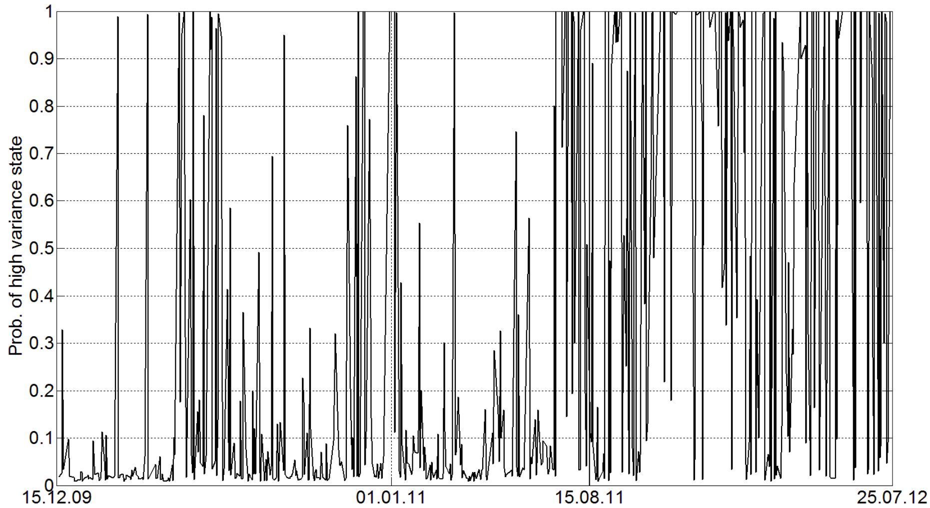

Figure IA.II: Normal mixture implied ex post probabilities (black) for the high conditional variance regime used for identification in the debt crisis sample (S_2: 15/12/2009 to 25/07/2012). The bold horizontal line displays the assumed change in unconditional variance (T_B: 15/08/2011) used for identification as described in Section 2.3.

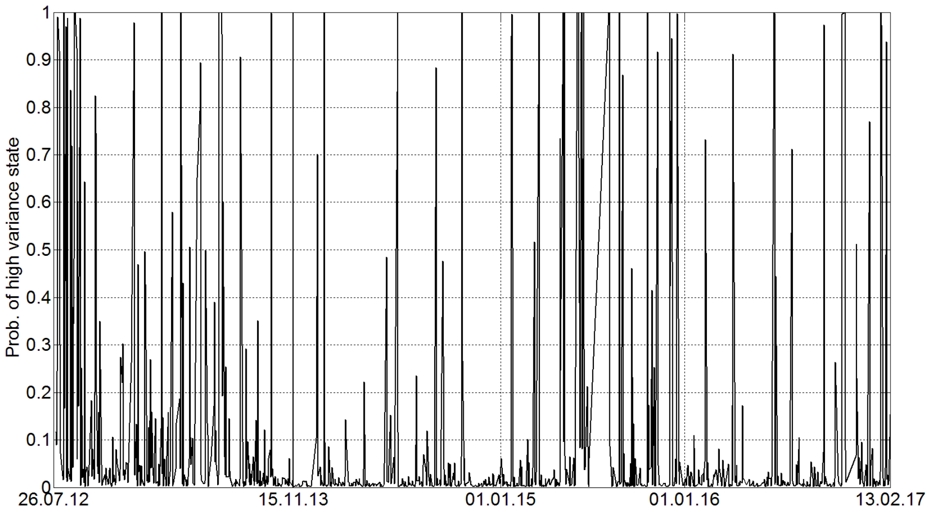

Figure IA.III: Normal mixture implied ex post probabilities (black) for the high conditional variance regime used for identification in the ECB announcement sample (S_3: 26/07/2012 to 13/02/2017). The bold horizontal line displays the assumed change in unconditional variance (T_B: 15/11/2013) used for identification as described in Section 2.3.

Table IA.I
Normal mixture implied estimates $\hat{\boldsymbol{B}}^{S*}$ for $(Germany_t, Spain_t, France_t, Italy_t)'$ and periods $S_1, ..., S_3$. Parameters significant at a 5% level in bold.

$$\hat{\boldsymbol{B}}^{1*} = \begin{bmatrix} \underset{}{1.000} & \underset{(0.119)}{-0.226} & \underset{(0.402)}{0.605} & \underset{(0.155)}{\mathbf{-0.698}} \\ \underset{(0.302)}{\mathbf{0.603}} & \underset{}{1.000} & \underset{(0.274)}{\mathbf{0.611}} & \underset{(0.187)}{-0.181} \\ \underset{(1.524)}{-0.404} & \underset{(0.111)}{-0.032} & \underset{}{1.000} & \underset{(0.135)}{\mathbf{-0.280}} \\ \underset{(0.390)}{0.631} & \underset{(0.114)}{0.028} & \underset{(0.294)}{\mathbf{0.700}} & \underset{}{1.000} \end{bmatrix}$$

$$\hat{\boldsymbol{B}}^{2*} = \begin{bmatrix} \underset{}{1.000} & \underset{(0.052)}{\mathbf{-0.185}} & \underset{(0.203)}{0.067} & \underset{(0.031)}{\mathbf{-0.199}} \\ \underset{(0.197)}{\mathbf{0.448}} & \underset{}{1.000} & \underset{(1.027)}{-0.590} & \underset{(0.083)}{\mathbf{0.522}} \\ \underset{(0.116)}{\mathbf{0.554}} & \underset{(0.321)}{0.171} & \underset{}{1.000} & \underset{(0.054)}{-0.015} \\ \underset{(0.109)}{\mathbf{0.385}} & \underset{(0.077)}{\mathbf{0.381}} & \underset{(0.385)}{-0.048} & \underset{}{1.000} \end{bmatrix}$$

$$\hat{\boldsymbol{B}}^{3*} = \begin{bmatrix} \underset{}{1.000} & \underset{(0.067)}{\mathbf{-0.231}} & \underset{(0.180)}{\mathbf{0.360}} & \underset{(0.100)}{\mathbf{-0.324}} \\ \underset{(0.222)}{\mathbf{0.640}} & \underset{}{1.000} & \underset{(0.147)}{\mathbf{0.569}} & \underset{(0.854)}{-0.625} \\ \underset{(0.485)}{-0.073} & \underset{(0.035)}{\mathbf{-0.103}} & \underset{}{1.000} & \underset{(0.094)}{-0.043} \\ \underset{(0.213)}{\mathbf{0.826}} & \underset{(0.177)}{\mathbf{0.601}} & \underset{(0.168)}{\mathbf{0.588}} & \underset{}{1.000} \end{bmatrix}$$

Table IA.I: This table is similar to Table 6, but shows Normal mixture implied estimates $\hat{\boldsymbol{B}}^{S*}$ for $(Germany_t, Spain_t, France_t, Italy_t)'$ and periods $S_1, ..., S_3$ with standard errors (in parentheses). Period S_1 is the interdependence sample running from 01/01/2001 until 14/12/2009. Period S_2 is the Euro crisis sample from 15/12/2009 to 25/07/2012. S_3 is the period after the ECB announcement from 26/07/2012 to 22/02/2017. Parameters significant at a 5% level are given in bold.

Chapter 3

FX pricing and strategic trading

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Abstract

We introduce a novel empirical framework to investigate the interdependencies between returns and trades. This scheme provides an unresticted estimate of instantaneous interactions of security demand and supply by employing differences in trade intensities. The framework is applied to a unique data-set covering 100 % of all end-user trades for the Brazilian Real/ U.S. Dollar market over six years including a natural experiment of an intervention and no-intervention period. For the latter asset traders exhibit an instantaneous profit-taking strategy and account for up to 72 % of FX return variation. For the former interventions come along with markedly reduced price informativeness.

Keywords: FX markets, FX pricing, strategic trading, FX interventions, mixture of normals hypothesis, statistical identification, conditional heteroscedasticity.

JEL classification: C32, C54, C58, F31, G12, G15

3.1 Introduction

The interdependence between returns and trades is of long-lasting interest to speculators as well as to liquidity providers and policy makers. This is the case since trades carry information and hence cause a persistent change in the security price.

Market participants are typically exposed to several dimensions of price uncertainty depending on the nature of the security and speculators may specialize in producing and trading on private information along these dimensions. For example, in our FX market case end-users have markedly distinct transaction motives. That is, foreign currency is traded because of an underlying cross border trade in assets or a trade in goods, respectively. In stock markets one may think of these dimensions as, e.g., the demand for a firms' products, success of technological innovations or the effects of macroeconomic developments influencing future cash flows.

However, trading produces informational flows and unless the information is publically revealed and hence fully priced other speculators may learn and benefit through trading on the same piece. Moreover, once prices move in the desired direction informed speculators may start reverting their positions. That is, in contrast to arbitrageurs speculators take risky positions and thus want to take profits and reduce exposure in a timely manner. As a consequence speculators have clear incentives to condition trades on both instantaneous price changes as well as on information about other dimensions of uncertainty that is still private and hence not fully priced.

In turn, large liquidity providers (market makers) face counterparty risk and need to quote prices for trades arriving from potentially informed speculators. Thus, they have clear incentives to identify informed groups of speculators. Moreover, they need to balance inventories and share risk with other participants.

Finally, if market makers are not able to unload inventory risk or fail in pricing new information correctly market liquidity and stability are at stake. In this case, policy makers may decide to intervene and thus to become part of the market interplay.

Todays the lion's share of volume in equity as well as foreign currency markets is generated from highfrequency trading.[1] Hence, with the arrival of news it is possible to manage positions and to revise price quotes within seconds or even shorter periods of time. As a result observed trade and return data most likely displays the outcome of multiple rounds of trades and price revisions as already suggested in Hasbrouck (1991b). However, when observing multiple trading rounds per unit time the need for an identification scheme without *a priori* restrictions on the instantaneous interdependencies between returns and trades raises dramatically.

We introduce a novel empirical framework to investigate the functioning and stability of speculative markets in matching demand and supply. For example, the interplay of both *trading strategies* of security seekers (speculators) and *price formation*, e.g., price setting rules of large liquidity providers (market makers) can be simultaneously revealed.

This scheme enables the investigator *inter alia* to pin down the absolute and relative importance of different dimensions of security price changes, speculator's trading styles and

[1]For example, as noted in Hendershott et al. (2011) already in 2009 algorithmic and thus high frequency trading was responsible for as much as 73% of the trading volume in the United States (see also, Easley et al. 2012).

strategies, market liquidity and stability, market maker pricing rules as well as rule-based interventions of policy makers. Thus, the interplay and performance of different types of speculators, market and policy makers in a speculative market's ecology is revealed.
However, in contrast to the existing empirical framework the investigator is freed from the burden of *a priori* assumptions regarding the interdependence pattern between returns and trades.
To appropriately answer on these questions in high frequency trading times we employ a vectorautoregressive (VAR) model and a novel identification scheme without *a priori* assumptions on non-existence or other restrictions on possible instantaneous informational flows between price (quote) changes and trades of asymmetrically informed participants. These *a priori* restrictions were a widely accepted standard procedure for decades[2], but come at unnecessary expense. In contrast, our suggested scheme allows the investigator to obtain a full picture of the interdependencies between returns and trades.
Moreover, VAR models are very flexible analytical tools. For example, they are robust to lagged adjustment to public and private information (See, e.g., Hasbrouck 1991a, b or Hendershott et al. 2011). That is, we inter alia control for auto- and lagged cross correlations in trades and price changes and head directly for the instantaneous informational surprises and news flows thereof.
The statistical analysis in this paper is built on the assumption that different market states can be identified, which are characterized by different degrees of *trading intensity* (similar to, e.g., Clark 1973; Hasbrouck, 1991b; and Evans, 2002).
More specifically, we employ a discrete version of the normal mixture approach in Clark (1973). In Clark's world, the leptokurtic properties of the return distribution stem from a varying rate at which new information is available to market participants. If this rate is low, the return process evolves slowly and vice versa. Thus, the return distribution is conditionally normal given the state of trading intensity, whereas it is non-normal unconditionally. In the spirit of Tauchen and Pitts (1983) we assume the same for orders and interventions in a multivariate normal mixture set up. Exploiting this distributional feature for identification we are able to provide an unrestricted estimate of instantaneous *price formation* and *trading strategies*.[3] In this our empirical model solves both the identification problem and Hasbrouck's (1991b) open task "‘(...) of constructing a single comprehensive specification that incorporates natural time effects (...)"’ like return heteroscedasticity. Moreover, based on this scheme trade intensity dependent impulse response functions and variance decompositions without restrictions on the *timing* of response become available.
Morover, following the mixture of normals hypothesis our modelling framework explicitly considers differences in the frequency of market events (trades and quote revisions) as compared

[2]see, e.g., Evans (2002) and Payne (2003) for the FX market case and Hasbrouck (1991a, 1991b)or Hendershott et al. (2011) for stock markets amongst many others. Typically, instantaneous feedback-trading is ruled out in bivariate systems of order flows and prices by *a priori* imposing recursive causalities.

[3]Moreover, in contrast to Hasbrouck (1991b) and Evans (2002), these low– and high trading intensity states are not "exogenously” assigned, but estimated from the same statistical model that provides the framework for structural identification.

to the observation frequency measured per unit time.[4]

For illustrative purposes, we resort to a unique data set provided by the Brazilian central bank, which has several particular merits. Firstly, it covers 100 % of all customer flows on a daily basis. It is widely accepted in the empirical order flow literature that primary market end-user flows have higher explanatory power than, e.g., inter-dealer flows. Moreover, in Kyle-type models like Froot et al. (1992), Hirshleifer et al. (1994) and Foucault et al. (2016) dealers are uninformed liquidity providers who set market clearing prices given the information contained in observed order flow records. That is, in our empirical model the price equation can be interpreted as the market makers pricing rule. Secondly, orders are disaggregated by transaction motive, i.e. for each trading day, we are able to calculate excess demand for U.S. dollars as motivated by underlying asset or goods transactions, or central bank interventions. As a result we are able to distinguish between two groups of informed end-users both providing information about a distinct trading dimension as in Froot et al. (1992) or Goldstein and Yang (2015). Finally, the period covered by the data embodies a natural experiment. The central bank only intervened during the first half of our six year observation period. This allows us to analyze the market interplay of trading strategies and price formation with and without central bank interventions.

The Brazilian FX market can be characterized as a highly concentrated two-tier over-the-counter (OTC) market, since OTC trading is possible in the bank-customer (primary) as well as in the interbank (secondary) market. However, these characteristics are quite standard for OTC markets and it might be worth noting again the proposed scheme is not limited to OTC or FX markets, but also well suited for the analysis of stock market workings in the vein of Hasbrouck (1991a, b) or Hendershott et al. (2011).

Our empirical evidence suggests that previously drawn restrictions may have lead to biased results on the interactions between returns and trades. Indeed, we find an interesting pattern of instantaneous informational flows from orders to prices and vice versa as well as between orders of differently informed participants. During the no-intervention period our results are in line with multiperiod strategic trading models á la Kyle (1985) like Froot et al. (1992) or Hirshleifer et al. (1994), while in intervention times they support the partial equilibrium, portfolio balance model as in Evans and Lyons (2002) and its extension in Killeen et al. (2006). Thus, the suggested scheme may improve our understanding of markets in situations where order flows and price change data are available at frequencies that may still be the aggregate outcome of multiple trading rounds (transactions and quote revisions; price changes).

The remainder of this paper is structured as follows. Section 3.2 discusses the related literature on informational flows between market participants. The following section 3.3 adresses the data and FX market organization in Brazil. Section 3.4 details the econometric model and how it helps to solve the identification problem. Moreover, econometric procedures used in estimation and inference are discussed. Section 3.5 presents the empirical results. Finally, section 3.6 concludes.

[4]For example, our FX data is observed on a daily frequency, but the number of events per day (transactions and quote revisions) may differ due to differences in information arrival and trade intensities.

3.2 Related literature

We aim for a comprehensive model of informational flows between speculative markets' participants, i.e. between asymmetrically informed end-users and liquidity providers (market makers). Moreover, our data covers two time periods which are characterized by the presence and absence of central bank interventions. Hence, we relate to three major strands of the literature, i.e. to price formation and trading strategies in speculative markets and the interplay of interventions with both.

In speculative markets the understanding of driving forces behind *price formation* is of enduring interest to participants as well as policy and market makers. According to the efficient market hypothesis (EMH), changes in security prices are driven by public informational surprises. These are typically measured by the unobservable (reduced form) price innovation.

However, as proposed in Hasbrouck (1991 a,b) this instantanous price innovation may be decomposed into a random walk and a trade related component. That is, in line with the EMH order flows are viewed as a prominent source of private informational surprises to the public. From an empirical view-point the importance of order flows for security pricing is also documented in Evans (2002), Evans and Lyons (2002, 2005) and Menkhoff et al. (2016) for foreign exchange (FX) and, e.g., by Hasbrouck (1991 a,b) and Hendershott et al. (2011) for stock markets.[5] Similarly, in theoretical Kyle-type models like Froot et al. (1992), Hirshleifer et al. (1994) and Foucault et al. (2016) potentially informed participants deal with large liquidity providers (market makers) who absorb order imbalances of security demand and supply.[6] In turn, market makers must learn private information from observed order flow records to quote appropriate clearing prices.[7] Thus, a natural question arising is the relative importance of public versus private information as drivers of price changes.

Moreover, several groups of participants may exist, each being privately informed about a different dimension of price uncertainty as in Froot et al. (1992) and Goldstein and Yang (2015). For example, in our FX market case end-users have markedly distinct transaction motives. Foreign currency is traded because of an underlying asset trade or a trade in goods with non residents. That is, participants may provide distinct fundamental FX price information on the balance of payments through their trades.

With differently informed participants additional questions of interest arise. For example, is there a group of traders whose private information is more valuable in the price setting of large liquidity providers and to which extent does their information affect clearing and hence market prices? Or are all dimensions of private information equally reflected in prices? That is, is there a high degree of information diversity and thus low uncertainty about fundamentals (see Froot et al. 1992 and Goldstein and Yang 2015)?[8]

[5] Typically, like in Kyle type models, prices are linear functions of order flows and the part of price change orthogonal to order information is interpreted as non private and hence as a public informational surprise. However, in these models trading strategies are linear functions, too.

[6] In Kyle-type models liquidity providers are assumed risk neutral, competitive and unable to disentangle informed and uninformed trades.

[7] If not they provide liquidity at a loss and in extreme cases may stop market making like during the US flash crash in May 2010 (c.f. Easley et al. 2012, Kirilenko et al. 2015).

[8] Related to this issue an explicit consideration of *trade intensities* allows a further key question in the field of *strategic trading* to be answered. That is, we are able to provide evidence on *strategic complementarities*

Thus, the relative importance of different sources of private information as drivers of price changes is of interest, too. That is, the reduced form price innovation needs to be decomposed into structural contributions stemming from several orthogonal private and public sources.
A second long-standing concern of the order flow literature is to present insights in the group specific *trading strategies* in causal response to both informational surprises stemming from differently informed participants and price changes due to public news. For instance, price changes in speculative markets may lead to *feedback-trading* as in Hirshleifer et al. (1994), Nofsinger and Sias (1999) and Feng and Seasholes (2004). However, in a non structural framework it is *a priori* unclear if this feedback-trading is in response to public (non trade related) information or if private information from differently informed participants is learned either directly or through the intermediation of a large dealer.
For example, as recently diagnosed in Menkhoff et al. (2016) different customer groups in FX markets may engage in risk sharing amoung each other through dealer intermediation. However, end-users may also become informed about other dimensions of price uncertainty through lunch talks as well as through the trading process. Nowadays high frequency trading is responsible for the lions share of volume in speculative markets (see, e.g., Hendershott et al. 2011 or Easley et al. 2012). Thus, there is no *a priori* reason why feedback-trading should not be present from an instantaneous perspective. That is, like the price, the instantaneous order innovation needs to be decomposed into structural contributions from different sources of information.
As frequently addressed from a theoretical perspective *timing and speed* matter for a profitable trading strategy (c.f. Froot et al. 1992, Hirshleifer et al. 1994 or Foucault et al. 2016). For example, in Hirshleifer et al. (1994) early informed participants are able to establish a short term profit-taking strategy. In contrast late informed participants just follow the leader. As a consequence early informed participants are able to reduce exposure in a timely manner and are able to share risk with and provide extra liquidity to late informed traders.
Clearly, with order flows and price changes aggregated to an arbitrarily high frequency yet still reflecting multiple rounds of trading, i.e. multiple transactions and quote revisions both price formation and trading strategies need to be discovered from the instantaneous perspective. Moreover, it is *a priori* unclear who leads and who follows, i.e. answering the question of instantaneous causalities between (daily) price changes and orders requires an unrestricted estimate of informational flows. Variance decompositions based on this unrestricted estimate may then also highlight differences in transmission speed and may give unbiased insights in strategy performance and market liquidity (depth).
Finally, what happens to price formation and trading strategies in times of central bank interventions? Do interventions directly affect FX prices or are there indirect channels at play? For example, Bikhchandani et al. (1992) show that a participant with superior information whose orders are observed by informed successors may induce a follow-the-leader strategy of the latter. The Brazilian central bank is informed early and perfectly about the order flow

versus *strategic substitutability.* More specifically we can answer the question, if more aggressive trading on own private information from one group of participants comes along with more or less aggressive trading from the other group.

record. Thus, an indirect intervention channel in the vein of Bikhchandani et al. (1992) or Hirshleifer et al. (1994) may be established leading to lower intervention costs. Moreover, Killeen et al. (2006) who build on the portfolio balance model of Evans and Lyons (2002) provide theoretical arguments for a dampening channel. That is, interventions may stabilize FX price volatility in line with the empirical findings in Reinhard (2000) and Calvo and Reinhard (2002). As a result inventory risk vanishes as well as order flow impact on FX prices. Thus, stabilizing FX volatility may come at the cost of lower information diversity in prices and thus higher uncertainty about underlying fundamentals.

3.3 Data and market organization

The organizational form of the market under investigation is of great importance, since it provides the rationale for the existence of information channels between participants. Moreover, the organizational structure might also lead to reasonable over-identifying restrictions in our framework. A detailed description of Brazilian FX markets may be found in Garcia et al. (2015), with the most important aspects relevant for the issues under study being summarized in the following subsection 3.3.1. Additionally, Figure 1 depicts the market organization and summarizes all possible directions of informational flows within the Brazilian FX market.

3.3.1 FX Market organization

The Brazilian spot market is divided into a primary and a secondary market. On the primary market, which is the one we observe, balance-of-payments transactions between residents and non-residents take place, where only financial institutions authorized by the central bank act as intermediaries. On the primary market trading is executed through specific contracts in bilateral conversations between counterparties. Order flows are earmarked as commercial or financial according to the nature of transaction, i.e. to trade goods or assets respectively with non-residents.

On secondary or interbank markets banks trade with each other for risk management purposes and liquidity needs. Trading in interbank markets is done over the counter (OTC), i.e. in bilateral conversations or through an electronic platform, where according to Garcia et al. (2015) a majority of 95 % of the gross volume is settled and transactions are registered without delay for regulatory purposes.[9]

The spot market is highly concentrated, i.e. 16 of 198 authorized banks accounted for 85 % of the total volume in 2014. The majority of commercial orders are traded by 86 non-financial institutions such as commercial banks. Thus, the interbank market provides a link between the commercial and the financial segment.

The Brazilian FX market is regulated by the Brazilian Central Bank (BCB) and order flow reporting is mandatory. Thus, the BCB has perfect knowledge concerning order flows from the real and financial economy. Until May 2012 the BCB intervened regularly and the FX

[9] This platform was introduced in April 2002 prior to our sample.

market is characterized as a managed float by Calvo and Reinhard (2002). Consequently, as suggested by sequential trading models, e.g., in Bikhchandani et al. (1992), Froot et al. (1992), Hirshleifer et al. (1994), Evans and Lyons (2002) or Killeen et al. (2006) the real and financial sector as well as the BCB may learn from each other over the course of the trading day. That is, for daily data it seems inappropriate to exclude *a priori* any information channels to solve the identification problem.

3.3.2 Data

The data set consists of daily observations for the period 11/05/2009 to 23/01/2015. Excluding non-trading days we have 1439 observations in total. As is typically done, we calculate net-positions of customer order flows (trades) as the difference between buying and selling positions.

Order flows are disaggregated into commercial (real economy) and financial economy order flows reflecting the underlying nature of transaction, i.e. to trade goods or assets with non-residents, respectively. Net-order flows (OF) as well as central bank interventions (Int) are denominated in million U.S. dollars (USD). Hence, a positive (negative) OF or intervention may be interpreted as an excess demand (supply) for foreign currency.

Additionally, percentage log returns of the Brazilian real (BRL) per unit USD spot rate are used. Hence, we have four endogenous variables: net-order flows from the real and financial sector, interventions and FX returns. These series are available to the public with a lag of one trading week from the SISBACEN database of the BCB.[10]

Reporting customer order flows is mandatory in Brazil. Hence, the data employed displays all primary market transactions during our sample period. We abstract from inter-dealer flows since the secondary market is not observed, but acts as a liquidity provider (c.f. Wu 2012). Moreover, since the order flow record is made public during the following week one might expect the learning process from private sources to be completed after this time at the latest. The BCB intervened in approximately 40 % of all trading days if the full sample is considered. Specifically, the BCB was not present in the second half of the sample, i.e. interventions took place only between 11/05/2009 until 02/05/2012 in approximately 76 % of all trading days, while for the period from 03/05/2012 to 23/01/2015 no interventions were observed. We split our sample accordingly and label the first and second periods as subsamples S_1 and S_2, respectively. As a consequence the underlying market structure with and without the central bank at play is revealed.

Table 1 summarizes subsample statistics for the series for S_1 and S_2 where one striking feature is the non-normality of the data throughout both samples.[11]

We control for the domestic (annualized SELIC baserate) and (virtually) for foreign interest rate (annualized federal funds baserate; FFR).[12] Additionally, we included the JP Morgan EMBI Spread for Brazil to control for the Brazilian sovereign risk premium as well the

[10] https://www3.bcb.gov.br/sgspub/localizarseries/localizarSeries.do?method=prepararTelaLocalizarSeries

[11] Especially the leptokurtic properties of the return, intervention and OF series back-up our assumption of a mixed normal distribution.

[12] There was no variation in the FFR during our sample.

Commodity Research Bureau's commodity price index and the Chicago Board of Equities volatility index (VIX). Control variables were drawn from datastream and included in first differences.

3.4 Econometric baseline model

Structural VAR models (SVAR) are typically used to investigate dynamic relationships between the elements of a K–dimensional vector of endogenous variables $\boldsymbol{y}_t$. In our baseline model, $\boldsymbol{y}_t = (Com_t, Fin_t, Int_t, \Delta FX_t)'$ in S_1, and $\boldsymbol{y}_t = (Com_t, Fin_t, \Delta FX_t)'$ in S_2, where Com_t, Fin_t, Int_t, and ΔFX_t denote net positions of commercial order flows (OF), financial OF, interventions, and FX log returns in period t, respectively.
Thus, in subsample S_1 we model end-user net orders from commercial and financial customers, central bank interventions and FX returns endogenously, while in sample S_2 the central bank does not intervene and is therefore excluded from y_t.
Adopting the notation of Amisano and Giannini (1997), we write the SVAR model of order p with autoregressive parameter matrices $\boldsymbol{C}_i$, $i = 1, \ldots, p$, as

$$\boldsymbol{y}_t = \boldsymbol{\nu} + \boldsymbol{C}_1 \boldsymbol{y}_{t-1} + ... + \boldsymbol{C}_p \boldsymbol{y}_{t-p} + \boldsymbol{D} \boldsymbol{z}_{t-1} + \boldsymbol{B} \boldsymbol{\epsilon}_t \tag{3.1}$$

where $\boldsymbol{z}_t$ is a vector of exogenous controls with impact coefficients $\boldsymbol{D}$[13] and $\boldsymbol{\epsilon}_t$ is a vector of zero–mean uncorrelated *structural* shocks at time t. That is, we consider commercial and financial customers (as well as the central bank) as having uncorrelated private information about the future market price developement. Uncorrelatedness reflects the idea of being asymmetrically informed about different dimensions of (price) uncertainty such as in the theoretical models of Froot, Scharfstein and Stein (1992) or Goldstein and Yang (2015).
The elements of the $K \times K$ matrix $\boldsymbol{B} = [b_{ij}]_{i,j=1,\ldots,K}$ are the contemporaneous reaction coefficients of the variables in $\boldsymbol{y}_t$ to the structural shocks in $\boldsymbol{\epsilon}_t$. That is, the element b_{ij} represents the instantaneous response of variable i to a unit shock in variable j. For example, the last row of the matrix $\boldsymbol{B}$ represents the FX return reaction function as a linear combination of surprise information from the sources considered in y_t. More explicitly, the last equation models the change in the market price in response to inter alia informational surprises from the end-user segment. Thus, like in Kyle-type models as, e.g., in Froot, Scharfstein and Stein (1992) and Hirshleifer et al. (1994) the FX return reaction function can be seen as the market makers pricing rule, where the expected clearing price change is conditioned on the observed order flows. Similarly, the first and the second row of $\boldsymbol{B}$ display commercial and financial customers' trading strategies in response to each others trades, interventions and return shocks (quote revisions). Notably, also Kyle (1985) focuses on the Bayesian Nash equilibrium, where all strategies are linear. Thus, the elements of matrix $\boldsymbol{B}$, which constitute the instantaneous

[13] Controls are included as lagged and hence predetermined variables to circumvent endogeneity issues; cf. the specification in Ülkü and Weber (2014), who analyze Turkish stock markets and order flows in a structural VAR. Hence, any instantaneous information from these controls is still included in the return innovations.

interplay of market participants are of primary interest in our analysis. Typically the VAR model is estimated in reduced form,

$$\boldsymbol{y}_t = \boldsymbol{\nu} + \boldsymbol{C}_1 \boldsymbol{y}_{t-1} + ... + \boldsymbol{C}_p \boldsymbol{y}_{t-p} + \boldsymbol{D} \boldsymbol{z}_{t-1} + \boldsymbol{u}_t \tag{3.2}$$

where the reduced form innovation vector $\boldsymbol{u}_t = (\boldsymbol{u}_{1t}, ..., \boldsymbol{u}_{Kt})'$ is given by

$$\boldsymbol{u}_t = \boldsymbol{B}\boldsymbol{\epsilon}_t, \quad \mathrm{Cov}(\boldsymbol{u}_t) = \boldsymbol{B}\,\mathrm{Cov}(\boldsymbol{\epsilon}_t)\boldsymbol{B}', \tag{3.3}$$

and $\mathrm{Cov}(\boldsymbol{\epsilon}_t)$ is diagonal. The goal is to identify the matrix $\boldsymbol{B}$ from the reduced form (3.2) and (3.3).

Traditionally, one has to rely on restrictions based on economic theory or *a priori* knowledge for identification of the structural relationships. For example, feedback-trading was *a priori* ruled out in Hasbrouck (1991a, 1991b), Evans (2002), Payne (2003) and Hendershott et al. (2011) by restricting the corresponding parameters in $\boldsymbol{B}$ to zero.[14] Thus, for the sake of identification any instantaneous and hence short-term trading strategies as, e.g., suggested by Froot et al. (1992) and Hirshleifer et al. (1994) are ruled out by assumption.

Such restrictions are hard to justify on a daily frequency. However, a full picture of the nature of interaction between different types of informed traders and their relative importance for FX price formation can only be inferred from an unrestricted estimate of $\boldsymbol{B}$.

Namely, following Lanne and Lütkepohl (2010), we exploit the non-normality of the data and allow $\boldsymbol{u}_t$ to follow a *scale* mixture of normal distributions with M states. The model can be written

$$\boldsymbol{u}_t \sim \begin{cases} \mathrm{N}(\boldsymbol{0}, \boldsymbol{\Sigma}_1) & \text{with probability} \quad \gamma_1 \\ \quad \vdots & \\ \mathrm{N}(\boldsymbol{0}, \boldsymbol{\Sigma}_M) & \text{with probability} \quad \gamma_M, \end{cases} \tag{3.4}$$

where $\mathrm{N}(\boldsymbol{0}, \boldsymbol{\Sigma})$ denotes a zero–mean multivariate normal distribution with covariance matrix $\boldsymbol{\Sigma}$, $\boldsymbol{\Sigma}_m \neq \boldsymbol{\Sigma}_n$ for $m \neq n$, and the strictly positive *mixing weights* or state probabilities γ_m satisfy $\sum_{m=1}^{M} \gamma_m = 1$. Then the overall density of $\boldsymbol{u}_t$ implied by (4) is not normal, but a mixture of normals, given by

$$f(\boldsymbol{u_t}) = \sum_{m=1}^{M} \gamma_m \phi(\boldsymbol{u}_t; \boldsymbol{0}, \boldsymbol{\Sigma}_m), \tag{3.5}$$

with $\phi(\boldsymbol{u}_t; \boldsymbol{0}, \boldsymbol{\Sigma})$ denoting the multivariate normal density with mean zero and covariance matrix $\boldsymbol{\Sigma}$. The class of normal mixtures gives rise to very flexible distributional forms and in particular exhibits excess kurtosis as typically found in financial data. Moreover, appealing to the 'mixture of normals' hypothesis of Clark (1973), the variance states can be interpreted as arising from a time-varying rate of surprise information leading to differences in trade

[14]More precisely, Hendershott et al. (2011) exclude contemporaneous returns from the order flow equation, which is equivalent to a zero restriction on $\boldsymbol{B}$; to rule out instantaneous feedback-trading.

intensities. The overall covariance matrix of $\boldsymbol{u}_t$ as implied by (3.5) is

$$\operatorname{Cov}(\boldsymbol{u}_t) = \sum_{m=1}^{M} \gamma_m \boldsymbol{\Sigma}_m. \tag{3.6}$$

All parameters of the distribution, i.e. the mixing weights γ_m as well as the distinct elements of the symmetric positive-definite covariance matrices $\boldsymbol{\Sigma}_m$, $m = 1, ..., M$, are simultaneously estimated from the data by maximum likelihood. That is, there is no *a priori* allocation of the observations to the variance states as, e.g., in Hasbrouck (1991b), Evans (2002), Rigobon (2003), or Ehrmann et al. (2011). Nevertheless, these states may be interpreted analogously to the market states of trading intensity as in Hasbrouck (1991b) or Evans (2002). The next subsection describes how these data properties can additionally be exploited to solve the identification problem in a way that results in an unrestricted estimate of the instantaneous perspective.

3.4.1 Identification

Historically, one way of coping with the problem of identifying the structural form of a VAR model was by drawing identifying restrictions to reduce the number of freely estimated structural parameters. For instance, in a bivariate system of aggregated orders and prices, feedback-trading was *a priori* ruled out by Hasbrouck (1991a, 1991b), Evans (2002), Payne (2003) or Hendershott et al. (2011) amongst others. Clearly, doing so results in an *a priori* neglect of certain transmission channels or other possibly unwarranted restrictions of the parameter space.

Moreover, in a system of disaggregated flows, one additionally has to take a stance on possibly instantaneous information transmissions between groups of asymmetrically informed participants. However, employing daily data, such restrictions are hard to justify in the era of electronic and algorithmic trading.

The recently developing literature on identification through heteroscedasticity takes a fresh look at the problem by increasing the number of linearly independent covariance equations instead, see, e.g., Rigobon (2003), Lanne and Lütkepohl (2010) or Herwartz and Lütkepohl (2014). Since we have a set of daily financial market data, and with the assumption of state–dependent trading intensities, an identification scheme exploiting the heteroskedasticity in the data becomes feasible. This scheme enables us to estimate the structural form without restricting the contemporaneous parameter space. Hence, we can allow for all possible directions of informational flows between market participants and prices.

Following Rigobon (2003), an exact identification of the underlying data generating process can be achieved, if at least two market states characterized by different volatility levels exist (see also Lanne and Lütkepohl 2008, Lanne et al. 2010 or Herwartz and Lütkepohl 2014). For this approach the following assumptions have to hold:

A1: Contemporaneous relationships between endogeneous variables/ structural innovations are stable across states, i.e. the $\boldsymbol{B}$–matrix is constant up to rescaling.

A2: Equations of state covariance matrices are linearly independent, i.e. shifts in variance between states are not proportional.

A3: Structural innovations are uncorrelated within all states, i.e. structural covariance matrices are diagonal.

If multiple (M) variance states exist, one can estimate M reduced form covariance matrices with each of them providing $K(K+1)/2$ equations. For example, if $K=4$ and $M=2$, they provide $2 \times [4(4+1)/2] = 20$ equations and, if $A2$ holds, one can identify 20 parameters. Thus, the $\boldsymbol{B}$–matrix of $K \times K$ contemporaneous causal effects can be identified. On the other hand, the K variances of the orthogonal structural innovations of one state are identified while the variances of the other state are normalized to one (or vice versa).
This (exactly) identifies a VAR model with K endogeneous variables, if (at least) $M=2$ states exist. Thus, instead of restricting the estimated parameter space, the amount of information, i.e. the number of linearly independent reduced form covariance equations, is increased by exploiting heteroscedastic properties.[15]
Now suppose we have two states. It is always possible to find a simultaneous decomposition $\boldsymbol{\Sigma}_1 = \boldsymbol{W I W'}$ and $\boldsymbol{\Sigma}_2 = \boldsymbol{W \Omega W'}$ with $\boldsymbol{\Omega} = diag(\omega_i)$ for $i = 1, ..., K$ and all $\omega_i > 0$ (see, e.g., Lütkepohl 1996, Golub and van Loan 1989). The elements on the main-diagonal of $\boldsymbol{\Omega}$ describe the shifts in variance of the structural innovations or shocks from the first to the second state. If $\omega_i \neq 1$, there has been a change in variance. Additionally, if $\omega_i \neq \omega_j$ for all $i \neq j$, then the change in variance is not proportional and assumption $A2$ holds. In this case, Matrix $\boldsymbol{W}$ is locally unique except for column-wise sign reversals. Actually, this means that one can specify the effects of either a positive or negative shock. If we set $\boldsymbol{W} = \boldsymbol{B}$, we obtain unique shocks $\boldsymbol{\epsilon}_t = \boldsymbol{B}^{-1}\boldsymbol{u}_t$, except for ordering.[16]
Assumption $A3$, i.e. orthogonality of the structural shocks, is satisfied since $E[\boldsymbol{\epsilon_t \epsilon_t}'] = \boldsymbol{I}_K$ in state 1 and $E[\boldsymbol{\epsilon_t \epsilon_t'}] = \boldsymbol{\Omega}$ in state 2. Thus the parameters in $\boldsymbol{B}$ can be interpreted as the initial response to a unit shock in the first state.
However, normalizing on the second state can be achieved straightforward by rescaling $\boldsymbol{B}$ via postmultiplication with $\boldsymbol{\Omega}^{\frac{1}{2}}$. As a consequence, matrices $\boldsymbol{B}$ normalized to different trade intensity states are in line with $A1$. Assumption $A1$ only becomes testable with over-identifying restrictions.[17]

3.4.2 Estimation and inference

The parameter vector $\boldsymbol{\theta}$ of the reduced form VAR is estimated by maximum likelihood (ML) via the EM–type algorithm discussed in McLachlan and Peel (2000) and Herwartz and Lütke-

[15] As noted in Rigobon (2003), since the residuals are elliptically distributed the shifts in variances provide us with a probabilistic instrument.
[16] As with any other identification strategy, the interpretation of the structural shocks and their relation to the endogenous variables has to be based on economic reasoning.
[17] Notably, $A1$ is also an (untested) assumption in Hasbrouck (1991a, 1991b) and Evans (2002), who also conditioned on different states of trading intensity and identified the matrix $\boldsymbol{B}$ in every market state by a Cholesky decomposition (ruling out feedback-trading). Nevertheless, we relax $A1$ by subsampling as described in subsection 3.3.2.

pohl (2014).[18] The appropriate number of states M and VAR order p are simultaneously choosen from information criteria such as AIC or BIC. Like in Broda et al. (2013) we focus on the BIC "(...), because the literature on mixture models provides some theoretical and empirical support for its appropriateness and good performance, in particular for selecting the number of mixture components" (see also, e.g., Keribin 2000; Francq et al. 2001; and Frühwirth-Schnatter 2006, Chapter 4).
Once the reduced form parameters have been estimated, the state-specific covariance matrices are simultaneously decomposed as $\hat{\boldsymbol{\Sigma}}_1 = \hat{\boldsymbol{B}}\hat{\boldsymbol{B}}'$, and $\hat{\boldsymbol{\Sigma}}_m = \hat{\boldsymbol{B}}\hat{\boldsymbol{\Omega}}_m\hat{\boldsymbol{B}}'$, $m = 2, \ldots, M$.[19] If more than two states are found, we propose to employing the two covariance matrices with the highest state probabilities, e.g., it might be possible especially for financial market data to find a state with very low probability, which is likely to reflect a number of outlier observations. That is, the aforementioned procedure may also be seen as a filter for outliers where the threshold is endogenously chosen. Clearly, doing so results in the omission of observations which, depending on the aim of the study, might be reasonable or not. However, if one is interested in 'on average effects', filtering outliers endogenously might be an advantage.[20] Hasbrouck (1991a, 1991b) also proposed filtering outliers.
Corresponding standard errors for $\hat{B}$, $\hat{\Omega}$ as well as for the VAR parameters $\hat{\beta}$ and $\hat{\gamma}_1, ..., \hat{\gamma}_{m-1}$ are drawn from the inverse of the Hessian of the observed log likelihood function, where covariances are reparameterized by observationally equivalent decomposition results. Standard errors for forecast error variance decompositions stem from a fixed design wild bootstrap procedure as in Goncalves and Kilian (2004). Further details for the case where identification is achieved through heteroscedasticity may be found in Lütkepohl and Herwartz (2014).
Before results are interpreted it is essential to check if the identification procedure was successful by testing whether there is evidence for enough pieces of identifying information from state–specific covariance structures. To test if equations of covariance matrices are linearly independent we use Wald tests of pair-wise equality of the structural variances ω_i. More formally we test $H_0 : \omega_i = \omega_j$ versus $H_1 : \omega_i \neq \omega_j$ for all $i \neq j$, where test statistics are asymptotically $\chi^2(k)$ distributed with k degrees of freedom equal to the number of restrictions under the Null. Assumption $A1$ has to stay untested until now, since in the best case we are exactly identified. Nevertheless, we relax $A1$ by subsampling as described in subsection 3.3.2.

3.5 Results

To simultaneously determine the number of states and lags we employ the BIC criterion. The BIC prefers the three- over the two-state mixture model with an optimal VAR order of $p = 2$

[18] Actually an extension of the EM algorithm known as the ECM (**E**xpectation–**C**onditional–**M**aximization) algorithm is used (Meng and Rubin, 1993), which is required due to the fact that with constant means across states, we cannot solve simultaneously for the parameters of the mean equation and the covariance matrices on each M–step. Thus the M–step is broken into two **c**onditional **m**aximization steps. In order to identify the global maximum of the likelihood function, a large number of random starting values have been generated to initialize the algorithm.
[19] Technical details for a simultaneous decomposition are given in the Appendix.
[20] However, in doing so results are still conditional on trade intensities, i.e. variance states.

for the first subsample S_1. We keep the specification constant in S_2 for comparability reasons. The resulting state probability estimates for this model are presented in Table 2. As can be inferred from the table the third state has a very low probability especially in S_1. Thus, we treat this state as an outlier state and use only states one and two for identification.[21]

Table 3 gives the corresponding structural variance estimates ω_i together with their standard errors. To check whether identification holds, we present Wald test results in Table 4. Pairwise tests for equality of structural variances under the Null are all rejected under standard criteria. Thus, there is evidence for exact identification in both S_1 and S_2.

As detailed in Section 3.4.1, as with any identification scheme, the ordering of the structural variances and columns in $\boldsymbol{B}$ must be accomplished by economic arguments, since reorderings of variance-column pairs are observationally equivalent. Our assumptions on the ordering are as follows.

As a general principle, informational surprises to the public shall have a significant impact on FX price changes.[22] Following a similar idea, a group of customers' private informational surprises should have a significant instantaneous impact on the groups' own information set. The same should hold for the central bank. These assumptions boil down to a statistically significant main-diagonal of $\boldsymbol{B}$ and are in line with the efficient market hypothesis.

Table 5a displays our column ordering in S_1. Given this general principle, columns 1 and 4 may still be interchanged. However, following the empirical findings in Reinhard (2000) and Calvo and Reinhard (2002), there exists an inverse relationship between structural variances of FX prices and currency reserves. For example, in order to stabilize FX prices, the monetary authority accepts a higher variance in reserves. We reestimated our baseline model in S_1 without order flows and find that an inverse relationship between intervention and FX return variances is also present in our data. Results from this exercise are discussed further in Section 3.5.3 and documented in the internet appendix. Since we already assigned a variance smaller than one to intervention shocks the remaining column corresponding to ω_4, which is greater than one, is assigned to the FX market shock.

The matrix $\boldsymbol{B}$ for subsample S_2 is given in Table 5b. Again, given a significant main-diagonal, the last column of this matrix could be exchanged with the second column. When doing so buying pressure for USD from the financial sector would causally lead to a decrease in FX returns and hence USD prices, which is implausible. The remaining two columns may again be ordered through the general principle stated above. Hence, a unique ordering of $\boldsymbol{B}$ is established in S_1 and S_2.

The next subsection presents the instantaneous or intra-day trading patterns with respect to participants' trading strategies and their interactions with price formation. Results are discussed in light of the theoretical literature and compared for the intervention and non intervention period. Furthermore, implications for risk sharing and market liquidity are sup-

[21] Corresponding reduced form variances in S_1 are highest in state 3 for commercial, financial order flows and FX returns, while the variance for interventions is comparable with the state 2 variance (high variance state). Moreover, as described in Section 3.5.3 overall results and especially the probability for state 3 is unchanged, if interventions are excluded from the model. Thus, there is evidence for outliers mainly in orders and FX returns.

[22] Regarding the nature of information in an efficient market framework, public surprise information should add significantly to the current (public) information set.

plied. Afterwards forecast error variance decompositions are discussed to characterize the dynamics of the formerly diagnosed intra-day effects. Special emphasis is given here to the relative price informativeness, information diversity reflected in prices, strategy performance as well as differences in group specific earliness of informedness and the advantages thereof.

3.5.1 Changes in intra-day trading patterns

The matrices $\boldsymbol{B}$ in Table 5a and 5b give row-wise instantaneous reaction functions of commercial, financial participants, the central bank and FX returns in the intervention period S_1 and the no intervention period S_2, respectively. Alternatively, they column-wise display the instantaneous impact of a unit trade and/ or price innovation in an informationally efficient market.

We normalized all columns to the effect of a positive unit shock in the first variance state. However, one can also normalize on the second state. In this case matrix $\boldsymbol{B}$ is just rescaled by post-multiplying with the diagonal matrix $\boldsymbol{\Omega}^{\frac{1}{2}}$.

Moreover, positive shocks are associated with a net buying pressure for USD from a group of market participants or with an increase in the BRL per unit USD return for a market shock, respectively. Since our model assumes symmetric shocks, one may just multiply single columns by minus one for the impact of a negative shock.

Pricing and trading strategies in intervention times

In S_1, we observe from the last row of the matrix $\boldsymbol{B}$ in Table 5a that only commercial customer net flows have a significant impact on FX returns, i.e. a (positive) unit shock to private real sector information leads to an 0.139% increase in FX returns on the same trading day. Interestingly, there is no instantaneous information-to-prices channel from financial net flows in S_1 nor from interventions. Moreover, as previously discussed and depicted in Table 3 structural variances of FX returns and interventions exhibit an inverse proportional relationship.

These findings are in line with the predictions of the portfolio balance model (PBM) in Evans and Lyons (2002) and Killeen et al. (2006), who extend the PBM to include central bank activity. With interventions the volatility of FX returns is reduced and hence the aggregate speculative demand or willingness to absorb FX risk gets perfectly elastic as FX volatility goes to zero. This indirect intervention channel is sometimes referred to as the 'dampening channel'. If FX volatility goes to zero holding foreign currency becomes effectively riskless. Thus, with interventions the portfolio balance channel originally proposed in Evans and Lyons (2002) is not operating. Moreover, in intervention times the price impact of order flow vanishes since it depends inversely on participants' aggregate willingness to absorb FX risk. As the latter gets perfectly elastic participants are willing to trade any amount of currency at a given price. In accordance with these arguments, our evidence suggests the group of financial customers act as pure liquidity providers due to central bank interventions and their stabilizing effect on FX volatility in S_1. In contrast commercial customer orders are not driven by

central bank activity nor is their price impact completely off-set.[23]
Additionally, we find financial orders to be driven by intervention shocks. Estimates in column three suggest the central bank is able to establish a second indirect intervention channel in that it is able to drive financial orders. Moreover, the same sign of the parameters suggests that financial customers follow the direction of interventions. Thus, we label this second indirect channel as the "signalling" channel. For instance, if the central bank sells BRL in an amount of 344 million U.S. dollars, financials exhibit an excess demand of 119 million U.S. dollars. Thus, financial customers' trading is a follow-the-leader strategy in S_1. Follow-the-leader trading has been shown to be a natural outcome in sequential trading, e.g., if previous trading decisions of participants with superior information are observerd as in Bikhchandani et al. (1992) or some participants receive information (about the fundamental value) later than others as in Hirshleifer et al. (1994). Clearly, being able to affect net orders is advantageous for a central bank since it reduces intervention costs.
Moreover, from the last column we observe positive feedback-trading from commercial customers, where a unit shock on FX returns corresponding to a depreciation of the domestic currency leads to an excess demand of 69.9 million U.S. dollar on the same trading day. Interestingly, this finding is in contrast with the PBM and in line with a safe haven effect. In Evans and Lyons (2002) market makers quote prices to the end of the trading day to induce negative feedback-trading from end-users. These quotes are the result of market makers' inventory imbalances and the liquidity demand thereof. However, the positive feedback-trading we find has negative consequences for market liquidity, since dealers are obviously unable to unload imbalances on end-users. In fact we find inventory imbalances are even amplified by commercial end-users. Clearly, the effects of central bank interventions we document above try to fill this gap. Thus, this safe haven effect can be seen as the reasoning why we find interventions are designed to enhance liquidity provision. It might be worth noting that the silence of the central bank reaction function in the third row is plausible. We interpret this finding as the result of discretionary rather than rule based interventions.
Nevertheless, we find financial customers to be heavily targeted by central bank interventions. As a result asset traders amplify intervention effects and provide extra liquidity to the market. However, the latter comes at the cost of higher price uncertainty, since private information from the asset trading dimension is not incorporated in prices. In contrast, commercial customers' intra-day trading remains essentially unaffected by central bank activity. That is, FX trades with an underlying trade in goods are not directly affected by interventions, but may profit from extra liquidity provided by financial end-users and the central bank.

Pricing and trading strategies without interventions

Table 5b summarizes reaction functions once the central bank is out of the market. As may be expected there are substantial differences in informational flows in comparison to S_1 especially

[23] Along the lines of the PBM this can be explained with a more inelastic willingness to absorb FX risk, which may stem from one or both of the following (a) a higher degree of risk aversion as compared to financial customers or (b) ignorance regarding the true risk exposure in intervention times.

with regard to financial customers and their FX market interactions.
Firstly, as presented in the last row of the $\boldsymbol{B}$ matrix in Table 5b a positive unit shock to financial orders associated with net buying pressure for U.S. dollar leads to an increase in BRL per unit USD returns of 0.779 % on the same trading day. Comparing unit shocks of the real and financial economy in S_2 we find a considerably smaller instantaneous impact on returns from the former of 0.107 %. Thus, from an intra-day perspective we find that private information from the financial economy is the leading driver of FX returns in S_2.
Secondly, from the last column of the matrix $\boldsymbol{B}$ in Table 5b we observe significant negative feedback-trading from the financial sector. In addition to a reduction in financial customers' risk exposure, this strategy results in extra liquidity provision from financial end-users to the market. Hence, there is evidence for financial customers to stabilize the FX market through a *profit-taking* strategy.
Finally, in column two of the same table we find intra-day information-signalling between both groups of market participants, where the real economy learns from financial orders and essentially trades in the same direction. Thus, in S_2 it is commercial customers who exhibit a *follow-the-leader* strategy. As noted in section 3.2 the resolution of our data is limited to the daily frequency. Thus, our empirical findings most probably display the outcome of multiple, sequential (intra-day) trading rounds. Hence, it may again be instructive to discuss our empirical picture of the market with respect to the theoretical literature on *strategic trading*.
In fact our integral findings fit very well to the set of theoretical predictions in Hirshleifer, Subrahmanyam and Titman (1994), where the key concept is the early informedness of one trader group. However, the Hirshleifer, Subrahmanyam, Titman (HST) model lags a unique reasoning for early informedness, while we find additional evidence in section 3.5.2 for financial customers to have a higher speed of information processing and thus being *early informed* investors compared to commercials. In the HST model early informed investors exhibit a *profit-taking* strategy, since they trade early and aggressively on superior information and revert their positions on favorable price moves already in the short-run. Thus, they are able to realize profits and reduce their risk exposure in a timely manner. Once the 'late informed' traders discover the superior information they are happy to take counterpart positions for those of the 'early informed' who already started to (partially) revert their positions, while the price is furtherly driven to the new (fundamental) value.
In light of the HST model our empirical findings suggest the interplay between financial and commercial customers already leads to significant risk sharing among both groups of end-users in the short run (through the intermediation of a large dealer). Additionally, it results in intra-day profit-taking and hence a reduction in risk exposure for financial customers and an additional liquidity provision from financial end-users to the market.[24]
Notably, previously employed standard procedures in the order flow literature would have failed to diagnose any feedback-trading or information-signalling from an instantaneous perspective for the sake of structural identification. If the assumption of no instantaneous

[24]The HST model assumes a common information signal, which is received with a time lag by different trader groups. In contrast, we assume the price reaction is a linear combination of private information from the asset and goods trading dimension in line with Froot et al. (1994) or Goldstein and Yang (2015). However, as a result trades are not just correlated like in HST, but caused by other trades and price moves.

feedback-trading like in Hasbrouck (1991a, 1991b), Evans (2002), Payne (2003) or Hendershott et al. (2011) is violated, the rest of the estimated parameter space is affected, too. Hence, also variance decompositions are invalid since they build on the estimate of the contemporaneous perspective. However, as we have documented above there are short-term strategies present in the OTC market. Thus, for the data under consideration here *a priori* assumptions on no feedback-trading or no information-signalling turn out to be invalid. The following subsection presents variance decomposition results based on our unrestricted estimate of the instantaneous perspective.

3.5.2 Price informativeness and strategic trading

Forecast error variance decompositions display the h-step ahead variation of a variable explained by shocks from different uncorrelated sources. For example, as noted by Hasbrouck (1991b) variance decompositions of FX returns or price changes constitute a natural measure for relative price informativeness of private versus public information. Clearly, if the effect of order variation on price changes is significant their effect on the price level is permanent (see also Evans 2002).[25]

Secondly, as also noted in Goldstein and Yang (2015) variance decompositions are an appropriate measure for information diversity of private information reflected in FX prices. In our set up, e.g., the variation of FX returns is traced back to private and public informational surprises, which stem from orthogonal sources namely from structural commercial and financial customer trade innovations, unexpected central bank interventions and price innovations, respectively.

Finally, variance decompositions for FX returns display the timing of price impact. Thus, they provide evidence on a group's earliness of informedness. In contrast, order flow decompositions may give further insights in strategy related issues. For example, the relative importance of FX price changes for orders of a profit-taker is a measure for strategy performance. Moreover, in the HST framework it is interpreted as an indicator for the proportion of late informed traders in the market.

With our identification scheme we are allowed to estimate the matrix $\boldsymbol{B}$ without any restrictions on instantaneous transmissions and thus on timing, e.g., we need not *a priori* rule out instantaneous feedback-trading and information-signalling to achieve an exact identification. Moreover, the normal mixture framework allows the presentation of decompositions for high and low trading intensities and by that may also answer traditional questions in the field of strategic complementarities vs. substituteability. That is, whether a higher trade intensity of one group of participants comes along with a higher or lower trading activity in another group, respectively.

[25] However, our empirical model is designed to describe price changes over horizons measured in trading days. This is in contrast to macro models for spot rate changes, where permanency is measured over months or longer.

Relative informativeness in intervention times

Table 6 to Table 9 summarize variance decompositions for $h = 1, ..., 20$ trading days a head for FX returns, financial, commercial customer net flows and interventions, respectively for subsample S_1 normalized to unit shocks in the first variance state.[26]
Table 6 displays variance decompositions for FX returns. From the last column of the table one can infer that a majority of 86.54 % of FX return variation is explained by public news shocks, while private information from commercial order flow shocks accounts for a share of 10.16 % of FX return variation. Intervention shocks as well as financial sector shocks have an economically insignificant influence on FX returns with 2.35 % and 0.95 % respectively. These findings are in line with central bank interventions and financial customers acting as pure liquidity providers in S_1. That is, only real sector information may be seen as a relevant driver for FX returns in S_1, while we find the financial sector information vanishes through the dampening channel of monetary policy.[27] Thus, variance decompositions of FX returns in S_1 underpin the role of financial customers as pure liquidity providers along the lines of the PBM. Nevertheless, this intervention induced liquidity provision comes at the cost of a sharp reduction in price informativeness as compared to the results of the no intervention sample discussed in the following subsection. Moreover, since financial customer information is not incorporated in FX prices in S_1 there is also a sharp reduction in information diversity reflected in prices. Thus, interventions also come at the cost of a higher price uncertainty from the asset trading dimension.
Table 7 shows decompositions for the financial sector. As already seen in the intra-day reactions financial customers learn from intervention shocks. Over a horizon of 20 trading days 8.97 % of financial order variation is driven by unexpected interventions. Thus, there is evidence for only a moderate effect of the signalling channel compared to the dampening channel of monetary policy over time.[28]
Table 8 displays decompositions for real economy order flow variation. As can be infered from the second column of the table real economy orders are mainly driven by shocks to the own private information set, where especially financial order and intervention shocks' influences are neglectable.To complete the picture Table 9 presents forecast error variance decompositions for BCB interventions. As can be inferred from the table nearly 100 % of intervention variation is explained by central bank private information. We interpret this finding as the result of discretionary rather than rule based interventions.

[26]To economize on space we abstract from presenting state 2 results for subsample 1 (S_1), which are comparable and available in the internet appendix Tables IA.I to IA.IV.

[27]The magnitude of the effect of order flows on prices is comparable with the results in Evans and Lyons (2005), where variance decompositions from an out-of-sample exercise are presented. Evans and Lyons (2005) utilized daily data for the USD/ Euro spot market for the period January 1993 to June 1999. During their sample period interventions from national central banks of the later members of the Euro–area took place regularly to fullfil the requirements of the European Monetary system (EMS). Thus, only a moderate impact of orders on prices in times of FX market interventions is also found there.

[28]Noteably, financial customers do not engage in feedback-trading due to return variation as can be infered from the last column of the table. This is another peace of evidence for the silence of the portfolio-balance channel of the PBM for this group of participants (and their relatively high willingness to absorb FX risk).

Relative informativeness without interventions

Tables 10 to 12 describe variance decompositions once the central bank has left the market. Results for this subsample (S_2) are again remarkably different from the intervention period. Table 10 gives decompositions for FX returns, where on the left hand side effects of a unit shock in the first variance state and on the right hand side effects of a unit shock in the second state are displayed.

As a first result we find the group individual share of private information from real and financial net positions for the explanation of FX returns varies across variance states. That is, *information diversity* reflected in FX prices depends on trade intensity states. Normalizing on the effect of a unit shock in the first state financial order shocks explain 72.07 % of FX return variation, while real economy shocks have a share of only 1.77 %. As displayed on the right hand side of Table 10, if one normalizes on the second state, the share of the former falls to 52.41 %, while the share of the latter rises to 17.99 %.

This finding is a result of *strategic substitutability*, i.e. of inversely switching trade intensities from the real and financial sector (c.f. right hand side of Table 3 for the estimates of the structural state variances). That is, if financial end-users trade more aggressively on their private information commercial customers trade less aggressively on their own information.[29] However, in subsample S_2 private information from asset trading is the main driver of FX returns in both states.[30]

In contrast, we find a constant *price informativeness* across trade intensity states. That is, in both states public information shocks account for approximately 30 % of FX return variation. In turn private information from order flows explains a majority of 70 %.[31] However, up to our reading we are the first to find a stable share of FX return variation attributable to private information flows across variance states. That is, we find a constant price informativeness across trading intensity states, but clear differences in information diversity.

Since we observe 100 % of primary market flows, i.e. all flows of active participants, these findings can be seen as evidence for market-wide constant short-run information *processing capacities*. That is, the Brazilian FX market may be seen as a mature market with a relatively large and constant number of participants.However, commercial customer variance decompo-

[29] We define trade intensity in line with Hasbrouck (1991b), where different states are related to the structural variances of order flow net positions and FX returns. However, with our methodological choice we abstract from arbitrary state definitions but estimate the unobservable trade intensity states directly from the data.

[30] When we compare these findings to the estimates of the structural variances for S_2 in Table 3 it turns out that a higher variance in net positions, i.e. a higher trade intensity is related to a higher share of FX return variation explained (and vice versa). It might be worth noting again that Table displays structural variance estimates of the second state relative to the first state, where variances are normalized to one. Thus, a variance estimate greater than one in the second state translates into an increase in variance from state 1 to state 2. Clearly, a higher structural variance comes along with a higher unit shock as also pointed out by Hasbrouck (1991b).

[31] –the magnitude of the relative price informativeness is in line with previous empirical results, e.g., from Evans (2002) and Evans and Lyons (2002), where the former found for a high trading intensity up to 80 % of FX price changes are explained by lagged and leading order flows. Notably, Evans (2002) employs the number of observed trades per period as a proxy for trade intensity and defines several market states accordingly. In doing so it is not clear whether a high trading intensity also reflects a high variation in excess demand for foreign currency or, e.g., balanced volume or turnover effects.

sitions discussed later give additional evidence in this direction.[32]

Moreover, variance decompositions for FX returns may also provide evidence on the relative *earliness of informedness.* As a consistent finding over subsample S_1 and S_2 the maximum impact of order flows on prices is reached at $h = 2$ trading days for real sector motivated trades and $h = 1$ for financial sector trades. This finding is invariant to states of high and low trading intensity (c.f. Tables 6, 10 and Table IA.I). Given the segmentation of the Brazilian FX market we interpret this result as an advantage in information processing of banks dealing mainly with financial assets compared to commercial and multiple banks and their respective end-users.[33] Clearly, the differences in information processing abilities indicate asset traders tend to be early informed (on average) compared to commercial traders, where Hirshleifer et al. (1994) showed our previously discussed trading strategies are a natural outcome thereof.

Table 11 provides decomposition results for financial orders. As can be inferred from column 4 and 7 the financial economy continues with feedback-trading in both market states, where an economically significant share of 61.08 % in state 1 and 70.16 % in state 2 are explained by FX return shocks. Thus, we find evidence for an excellent *performance* of financial customers' profit-taking strategy. They are therefore able to significantly reduce own risk exposure over time by reverting their positions on (favorable) price moves in S_2.[34] However, in the HST framework profit-taking should be more strongly evident with a larger proportion of late informed traders.

Finally, Table 12 gives decomposition results for real sector flows. As depicted on the left hand side of the table there is information-signalling from the financial to the real economy in the first variance state. In this state trade intensity of financials is high compared to the commercial intensity. Accordingly, 14.47 % of real economy order variation is driven by surprises from the financial economy in the first state, while in the second (low financial sector variance) state this share declines to an economic insignificant value of 1.27 %. Thus, from forecast error variance decompositions we find evidence for commercial customers to continue with a *follow-the-leader* strategy on subsequent trading days, when financial customers' trade intensity is comparably high. That is, when financial end-users trade more aggressively on their private information or more information is produced in asset trading commercial end-users are deterred from trading on private information from the goods trading dimension. Instead, we find learning capacities from commercials are redirected to the asset trading dimension.

3.5.3 Robustness checks

Our baseline microstructure model in the system of equations (1) already controls for several (predetermined) global and local macroeconomic influences as well as first and second moment

[32]That is, we find further evidence for *strategic substitutability*, where commercial end-users trade less on their own private information, if the trade intensity from the asset dimension is high. Instead, they (partially) redirect their information processing capacities and learn from asset trade related information.

[33]These results are fairly in line with the results in Menkhoff et al. (2016) concerning the speed of information processing, the superior ability of financial customers to process information and the informativeness of order flows from financial compared to commercial customers.

[34]This finding stands in stark contrast to S_1, where in line with the extension of the PBM from Killeen, Lyons and Moore (2006) a non operating portfolio balance channel is diagnosed.

interactions.[35] Nevertheless, we check it against several alternatives.
Firstly, the breakdown of the information-to-prices channel from the financial economy as well as the possible existence of indirect intervention channels in the first subsample is of special interest. Since our model deviates apart from our identification scheme mainly in the consideration of interventions as an endogenous variable we reestimate the baseline model without including interventions. If those were a missing variable in previous studies, e.g., in Evans (2002) or Evans and Lyons (2002, 2005) one might suggest finding the information-to-prices channel in this case.
As a second exercise we estimate a bivariate system of interventions and FX returns to see whether the missing link, namely order flows, leads to a significant direct intervention channel. Moreover, from this exercise we provide additional evidence on the inverse relationship between FX return and intervention variances we used for ordering. As a drive by we also provide evidence for which of the endogenous variables order flows, interventions or FX returns are the main source for outliers in S_1.
As a third exercise we control our baseline specification in (1) for weekday effects by including dummy variables in both subsamples. For brevity results are just summarized here, while tables are available in the Internet appendix.

Baseline model excluding interventions

In an alternative model, which *ceteris paribus* excludes interventions from the set of endogenous variables there is some doubt if an exact identification has been achieved given Wald test results for equality of structural variances, where one p-value is above the 10 % significance level.[36] However, if we rely on numerically different structural variances like in Rigobon (2003) or Ehrmann et al. (2011) amongst others we find forecast error variance decompositions for FX returns to be qualitatively and quantitatively unchanged.[37]
Thus, the poor performance of order flows in explaining variation of FX returns in comparison to S_2 is not attributable to the presence of the intervention variable in the model[38], but rather results from an indirect intervention channel. Moreover, the probability for observing an outlier observation γ_3 is remarkable stable, too.[39] Hence, outliers are not produced by central bank interventions, but are inherent to order flows and/ or FX returns. However, the baseline model results are fairly robust to the exclusion of interventions in S_1.

Baseline model excluding order flows

In a bivariate system of interventions and FX returns it turns out the ECM algorithm is not able to estimate a three state model because of singularity issues. This problem typically occurs in situations where one wants to estimate more mixture states then supported by

[35] The VIX as a measure for global volatility is included in the mean equations of the VAR.
[36] c.f. Internet appendix Table IA.VIII
[37] c.f. Internet appendix Table IA.X
[38] In the sense of any multicollinearity problems between the intervention and financial order flow series.
[39] c.f. Table IA.VI

the data and thus the probability of the last state is undistinguishable from zero. However, together with the previous check we may conclude that outliers are mainly found in the order flow series in S_1.[40]
When estimating the same bivariate model with two mixture states the inverse relationship of intervention and FX return variances we used for our column ordering in the baseline model still exists.[41] Moreover, instantaneous as well as lagged transmissions between interventions and FX returns do not change compared to the baseline specifications.[42] Thus, there is additional evidence for interventions to work, if anything through an indirect channel, i.e. by affecting order flows rather than FX returns directly.

Baseline model with weekday controls

As frequently discussed in the literature time-of-day as, e.g., in Evans (2002) or weekday specific effects (e.g., in McFarland et al. (1982) or So (1987) amongst others) may be considered. Since the data under consideration is on a daily frequency we control for weekday effects by including dummy variables for Mondays, Tuesdays, Wednesdays and Thursdays in our system of equations (1). However, the results of our baseline model are not sensitive to weekday effects in S_1 nor in S_2.[43]

3.6 Conclusions

The aim of this work is to enlighten the instantaneous directions of informational flows in a speculative market with asymmetrically informed end-users and large liquidity providers (market makers). In contrast to the existing literature the contemporaneous perspective does not require a set of *a priori* restrictions on information transmissions.
In particular feedback-trading and information transmissions between asymmetrically informed participants are not ruled out from an instantaneous perspective. Thus, the timing of participants' and market maker response to informational surprises is not restricted.
Instead, we use recent advances in SVAR methodology and data-inherent information from heteroscedasticity to achieve an unrestricted estimate of transmissions. Moreover, simultaneously estimated variance states are interpreted in line with market states of trading intensity. However, this scheme is appropriate, e.g., when order flow and price change data are available at time frequencies that may still be the aggregate outcome of multiple trading rounds (transactions and quote revisions).
Our results suggest timing and earliness of informedness is the key to establishing a profitable trading strategy. We find financial (asset) traders are on average early informed compared to commercial (goods) traders. Moreover, the former trade early and aggressively on own private information and instantaneously revert their positions on favorable price moves. Information from the asset trading dimension accounts for up to 72 % of FX return variation. In contrast,

[40] Also Menkhoff et al. 2016 diagnosed outliers in their order flow series. However, they claimed their results are not sensitive to non exclusion.
[41] c.f. Table IA.XIV
[42] c.f. Tables IA.XVII to IA.XVIII
[43] c.f. Tables IA.XIX to IA.XXX

commercial end-users are on average late informed and in line with Hirshleifer et al. (1994) follow the direction of orders from early informed asset traders. Thus, financial customers are able to reduce their overnight exposure and to share risk with commercial customers. Moreover, as a result of this short term strategy asset traders stabilize FX price developments and provide extra liquidity by reverting their positions in a timely manner. We also find evidence for this profit-taking strategy to perform well, since up to 70 % of financial order variation is due to feedback-trading. In line with Hirshleifer et al. (1994) the latter result also points towards a large proportion of late informed traders.

However, in intervention times market dynamics are different. We find the central bank is able to establish two indirect intervention channels both targeting financial end-users. Firstly, financial end-users instantaneously follow the direction of interventions. As a result intervention costs of the central bank are reduced and intervention effects amplified. Secondly, a higher variance in interventions comes along with a lower FX return variance and higher trade intensites from end-users. Moreover, also in line with the dampening channel proposed in Killeen et al. (2006) we find the price impact of financial end-users is completely off-set. That is, we find that financial customers act as pure liquidity providers in intervention times. Thus, interventions come at the implicit costs of lower information diversity reflected in FX prices and at the benefit of higher market depth.

As a consistent finding over sub samples and trade intensity states financial end-users appear to be early informed on average compared to commercial customers. Moreover, in non intervention times we find a stable price informativeness of private information across trade intensity states. Taken together with the fact that we observe the complete end-user order flow record we view this as evidence for constant information processing capacities in a mature FX market. However, we find information diversity is conditional on trade intensity states. In times of a high rate of information arrival from the asset trading dimension commercial customers redirect information processing capacities and learn from financial orders. As a consequence information from the goods trading dimension is not reflected in FX prices when the rate of information arrival from the asset trading dimension is high.

Given our identification scheme we find both possible instantaneous causal directions between FX price changes and order flows in intervention as well as no intervention times. That is, an *a priori* assumption of no instantaneous feedback from prices to orders is found to be inappropriate for daily data. Moreover, we document a rich pattern of information transmissions between asymmetrically informed participants. Consequently, one needs to determine price formation and trading strategies simultaneously from the instantaneous perspective.

With our methodological choice we are able to provide a detailed picture of the ecology and efficiency of an otherwise opaque market from one comprehensive model. Moreover, the revealed trading strategies suggest investors have a clear incentive to enhance their speed of information processing. It might be worth noting again that our evidence does not speak against an efficient market, since order flow information is non-public (See, e.g., Evans and Lyons 2005). In general, information-based feedback-trading is rational, too (As, e.g., in Froot et al. 1992, Bikhchandani et al. 1992, Hirshleifer et al. 1994, Nofsinger and Sias 1999, Feng and Seasholes 2004 and Hendershott et al. 2011).

3.7 References

Amisano, G. and C. Giannini, 1997. *Topics in Structural VAR Econometrics*, Berlin: Springer.

Bikhchandani, S., Hirshleifer, D. and I. Welch, 1992, A theory of fads, fashion, custom, and cultural change as informational cascades, *Journal of Political Economy* 100, 992-1026.

Broda, S. A., Haas, M., Krause, J., Paolella, M. S. and S. C. Steude, 2013, Stable mixture GARCH models, *Journal of Econometrics*, 172, 292-306.

Calvo, G. A. and C. M. Reinhart, 2002, Fear of Floating, *The Quarterly Journal of Economics*, 117, 379-408.

Clark, P. K., 1973, A subordinated stochastic process model with finite variance for speculative prices, *Econometrica*, 41, 135-155.

Easley, D., Lopez de Prado, M. M. and M. O'Hara, 2012, Flow Toxicity and Liquidity in a High-frequency World, *Review of Financial Studies*, 25, 1457-1493.

Ehrmann, M., Fratzscher, M. and R. Rigobon, 2011, Stocks, bonds, money markets and exchange rates: Measuring international financial transmission, *Journal of Applied Econometrics*, 26, 948 - 974.

Evans, M. D., 2002, FX Trading and Exchange Rate Dynamics, *Journal of Finance* 62, 2405-2447.

Evans, M. D. and R. K. Lyons, 2002, Order flow and exchange rate dynamics, *Journal of Political Economy* 110, 170-180.

Evans, M. D. and R. K. Lyons, 2005, Meese-Rogoff Redux: Micro-Based Exchange-Rate Forecasting, *The American Economic Review*, 95, 405-414.

Feng, L. and M. S. Seasholes, 2004, Correlated Trading and Location, *Journal of Finance*, 59, 2117-2144.

Foucault, T., Hombert, J. and I. Rosu, 2016, News Trading and Speed, *Journal of Finance*, 71, 335-382.

Froot, K. A., Scharfstein, D. S. and J. C. Stein, 1992, Herd on the street: Informational inefficiencies in a market with short-term speculation, *Journal of Finance* 47, 1461-1484.

Francq, C., Roussignol, M. and J.-M. Zakoian, 2001, Conditional heteroskedasticity driven by hidden Markov chains, *Journal of Time Series Analysis*, 22, 197-220.

Frühwirth-Schnatter, S., 2006, *Finite Mixture and Markov Switching Models*, Springer: New York.

Garcia, M., Marcelo, M. and F. Santos, 2015, Price discovery in brazilian FX markets, *Brazilian Review of Econometrics*, 35, 65-94.

Goldstein, I. and L. Yang, 2015, Information diversity and complementarities in trading and information acquisition, *Journal of Finance* 70, 1723-1764.

Golub, G. H. and C. F. Loan, 1989, *Matrix Computations*, Baltimore: The Johns Hopkins University Press.

Goncalves, S. and L. Kilian, 2004, Bootstrapping autoregressions with conditional heteroskedasticity of unknown form. *Journal of Econometrics*, 123, 89-120.

Hasbrouck, J., 1991a, Measuring the Information Content of Stock Trades, *The Journal of Finance*, 46, 179-207.

Hasbrouck, J., 1991b, The Summary Informativness of Stock Trades: An Econometric Analysis, *The Review of Financial Studies*, 4, 571-595.

Hendershott, T., Jones, C. M. and A. J. Menkveld, 2011, Does Algorithmic Trading Improve Liquidity?, *The Journal of Finance*, 66, 1-33.

Herwartz, H. and H. Lütkepohl, 2014, Structural vector autoregressions with Markov switching: Combining conventional with statistical identification of shocks, *Journal of Econometrics* 183, 104-116.

Hirshleifer, D., Subrahmanyam, A. and S. Titman, 1994, Security analysis and trading patterns when some investors receive information before others, *Journal of Finance* 49, 1665-1698.

Keribin, C., 2000, Consistent estimation of the order of mixture models, *Sankhya: The Indian Journal of Statistics*, Series A62(1), 49-66.

Killeen, W. P., Lyons, R. K. and M. J. Moore, 2006, Fixed versus flexible: Lessons from EMS order flow, *Journal of International Money and Finance* 25, 551-579.

Kirilenko, A., Kyle, A. S., Samadi, M. and T. Tuzun, 2015, The Flash Crash: High Frequency Trading in an Electronic Market, *Journal of Finance*, forthcoming.

Kyle, A. S., 1985, Continuous Auctions and Insider Trading, *Econometrica*, 53, 1315-1335.

Lanne, M. and H. Lütkepohl, 2008, Identifying Monetary Policy Shocks via Changes in Volatility, *Journal of Money, Credit and Banking*, 40, 1132-1149.

Lanne, M. and H. Lütkepohl, 2010, Structural Vector Autoregressions With Nonnormal Residuals, *Journal of Business & Economic Statistics*, 28, 159-168.

Lanne, M., Lütkepohl, H. and K. Maciejowska, 2010, Structural Vector Autoregressions with Markov Switching, *Journal of Economic Dynamics and Control*, 34, 121-131.

Lütkepohl, H., 1996, *Handbook of Matrices*, New York: Wiley and Sons.

McFarland, J. W., Richardson Pettit, R. and S. K. Sung, 1982, The Distribution of Foreign Exchange Price Changes: Trading Day Effects and Risk Measurement, *Journal of Finance*, 37, 693-715.

Mc Lachlan, G. and D. Peel, 2000. *Finite Mixture Models*, New York: Wiley.

Meng, X. L. and D. B. Rubin, 1993, Maximum Likelihood Estimation via the ECM Algorithm: A General Framework. *Biometrika*, 80, 267-278.

Menkhoff, L., Sarno, L., Schmeling, M. and A. Schrimpf, 2016, Information Flows in Foreign Exchange Markets: Dissecting Customer Currency Trades, *The Journal of Finance*, 71, 601-634.

Nofsinger, J. R. and R. W. Sias, 1999, Herding and Feedback Trading by Institutional and Individual Investors, *The Journal of Finance*, 54, 2263-2295.

Payne, R., 2003, Informed trade in spot foreign exchange markets: an empirical investigation, *Journal of International Economics* 61, 307-329.

Reinhart, C. M., 2000, The Mirage of Floating Exchange Rates, *The American Economic Review*; 90, 65-70.

Rigobon, R., 2003, Identification through Heteroscedasticity, *The Review of Economics and Statistics*, 84, 777-792.

Tauchen, G. E. and M. Pitts, 1983, The Price Variability-Volume Relationship on Speculative Markets, *Econometrica*, 51, 485-505.

So, J. C., 1987, The Distribution of Foreign Exchange Price Changes: Trading Day Effects and Risk Measurement - A Comment, *Journal of Finance*, 42, 181-188.

Ülkü, N. and E. Weber 2014, Identifying the Interaction between Foreign Investor Flows and Emerging Stock Market Returns, *Review of Finance*, 18, 1541-1581.

Wu, T., 2012, Order flow in the South: Anatomy of the Brazilian FX market, *North American Journal of Economics and Finance*, 23, 310-324.

3.8 Appendix

Appendix A: Figures

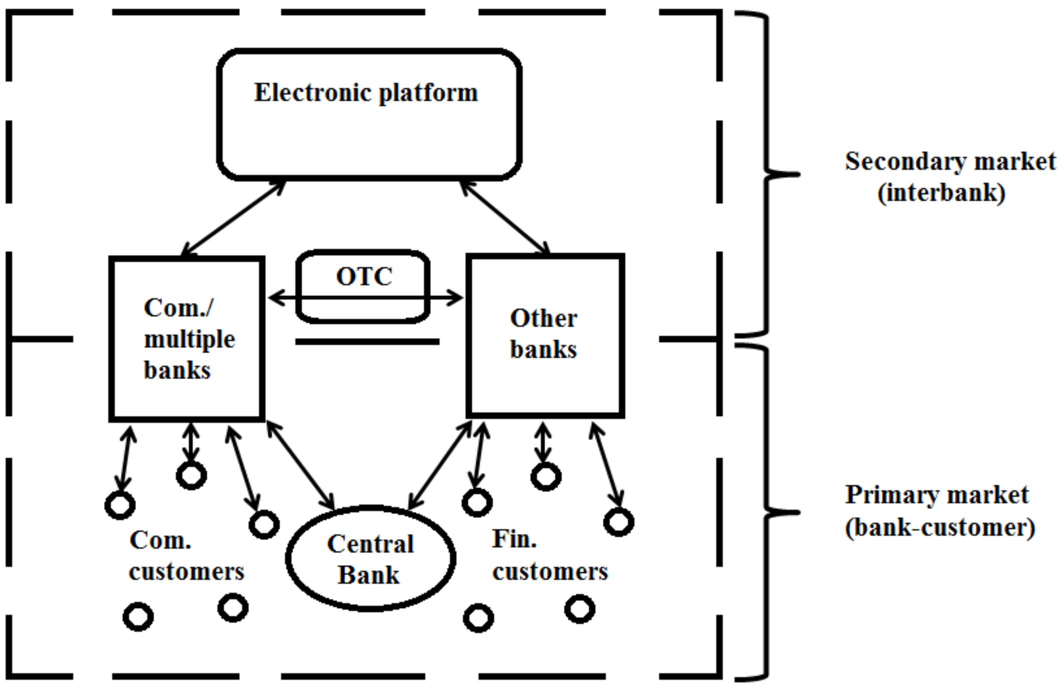

Figure 1: Brazilian spot market organization. Double arrows indicate possible bidirectional informational flows from over-the-counter (OTC) trading. Informational flows from OTC trading are possible between customers and banks in the primary market. The secondary market provides an OTC link between banks.

Appendix B: Tables

Table 1

Descriptive statistics and Jarque-Bera test results

	S_1				S_2		
	Com_t	Fin_t	Int_t	ΔFX_t	Com_t	Fin_t	ΔFX_t
Mean	74.879	106.904	160.860	-0.011	5.521	-50.569	0.044
Min	- 2252.000	- 2405.000	0.000	-2.800	- 1138.000	- 3037.000	-3.400
Max	1752.000	6671.000	1453.000	3.900	3773.000	3674.000	3.500
Std.-Dev.	400.6255	692.7637	237.4827	0.7847	440.8577	619.5932	0.7069
Skewness	0.2519	2.3422	2.3870	0.4553	1.7991	0.2273	-0.1624
Kurtosis	6.5480	18.4632	9.3369	5.5279	12.5190	7.0068	6.0046
JB-Stat ($p-value$)	4.013×10^2 (0.000)	8.158×10^3 (0.000)	1.967×10^3 (0.000)	2.256×10^2 (0.000)	2.973×10^3 (0.000)	4.668×10^2 (0.000)	2.622×10^2 (0.000)

Table 1: Descriptive statistics and Jarque-Bera test results for unconditional normality of the endogeneous variables $y_t = (Com_t, Fin_t, Int_t, \Delta FX_t)'$, where Com_t are net positions of order flows from the real economy, Fin_t are net positions in order flows of the financial economy, Int_t are interventions all denominated in million U.S. dollar. Net positions are calculated as buying minus selling positions and thus a positive (negative) sign reflects an excess demand (supply) for foreign currency. Similarly, a positive (negative) intervention sign reflects an excess demand (supply) for foreign currency. ΔFX_t is the log return of the Brazilian real per unit U.S. dollar FX rate. Calculations are presented for the period 11/05/2009 to 02/05/2012 denoted as S_1 in column 2 - 5 and period 03/05/2012 to 23/01/2015 denoted as subsample two S_2 in column 6 - 8. **Mean** is the mean of the series. **Min**, **Max** is the minimum and maximum observation of the respective period. **Std.-Dev.** is the standard deviation of the series. **Skewness**, **Kurtosis** is the skewness and kurtosis, respectively. **JB-Stat** is the test statistic with corresponding p-value of the Jarque-Bera test for normality under the Null hypothesis.

Table 2

Estimates of state probabilities γ_m for S_1 and S_2

with number of states $M = 3$ and lag order $p = 2$.

	S_1		S_2	
Parameters	**Estimate**	**Std-Dev.**	**Estimate**	**Std-Dev.**
γ_1	0.345	0.035	0.257	0.051
γ_2	0.591	0.036	0.635	0.051
$\gamma_3 = 1 - \gamma_1 - \gamma_2$	0.064	-	0.107	-

Table 2: Estimates of state probabilities γ_m for states $i = 1, ..., M$. S_1 denotes period 11/05/2009 to 02/05/2012 and S_2 denotes the period 03/05/2012 to 23/01/2015 with number of states $M = 3$ and lag order $p = 2$, where M and p are simultaneously chosen from the Schwarz information criterion in S_1 and kept constant for reasons of comparability in S_2. **Estimate**, **Std-Dev.** is the parameter estimate and corresponding standard deviation, respectively.

Table 3

Estimates of structural variances ω_i corresponding to $u_t = (Com_t, Fin_t, Int_t, \Delta FX_t)'$ in S_1

and $u_t = (Com_t, Fin_t, \Delta FX_t)'$ in S_2

	S_1		S_2	
Parameters	**Estimate**	**Std.-dev**	**Estimate**	**Std.-dev**
ω_1	0.714	0.125	2.048	0.542
ω_2	0.341	0.054	0.147	0.025
ω_3	0.022	0.004	-	-
ω_4	2.524	0.362	0.229	0.039

Table 3: Estimates of structural variances ω_i for $i = 1, ..., K$ endogeneous variables corresponding to $u_t = (Com_t, Fin_t, Int_t, \Delta FX_t)'$ for period 11/05/2009 to 02/05/2012 denoted S_1 and $u_t = (Com_t, Fin_t, \Delta FX_t)'$ for period 03/05/2012 to 23/01/2015 denoted S_2. **Estimate**, **Std-Dev.** is the parameter estimate and corresponding standard deviation, respectively.

Table 4

Wald tests for equality of ω_i from Table 3

	S_1		S_2	
H_0	**test statistic**	**p-value**	**test statistic**	**p-value**
$\omega_1 = \omega_2$	7.355	0.007	12.309	0.001
$\omega_1 = \omega_3$	29.927	0.000	-	-
$\omega_1 = \omega_4$	24.149	0.000	11.388	0.001
$\omega_2 = \omega_3$	34.124	0.000	-	-
$\omega_2 = \omega_4$	36.268	0.000	3.061	0.080
$\omega_3 = \omega_4$	47.502	0.000	-	-

Table 4: Wald test results for a equal change in structural variances from Table 3. $H_0: \quad \omega_i = \omega_j$ for all $i \neq j$ is the Null of pairwise-equality of state two variances. S_1 denotes results for the period 11/05/2009 to 02/05/2012 and S_2 for period 03/05/2012 to 23/01/2015, respectively. **test statistic**, **p-value** are the corresponding test statistic and p-value.

Table 5a

Estimated instantaneous reaction functions; B matrix for $u_t = (Com_t, Fin_t, Int_t, \Delta FX_t)'$ corresponding to the ordering of the ω_i in Table 3 with Standard errors in parentheses. Period S_1: 11/05/2009 - 02/05/2012.

$$\hat{B} = \begin{bmatrix} \underset{(21.755)}{345.504^{***}} & \underset{(59.403)}{6.076} & \underset{(25.563)}{31.808} & \underset{(18.742)}{69.909^{***}} \\ \underset{(73.139)}{-71.502} & \underset{(37.401)}{642.594^{***}} & \underset{(48.904)}{119.878^{***}} & \underset{(18.464)}{5.815} \\ \underset{(4.003)}{-1.742} & \underset{(6.637)}{-7.520} & \underset{(20.293)}{344.038^{***}} & \underset{(1.804)}{-0.296} \\ \underset{(0.057)}{0.139^{**}} & \underset{(0.051)}{0.049} & \underset{(0.038)}{0.017} & \underset{(0.027)}{0.493^{***}} \end{bmatrix}$$

Table 5a: Estimated instantaneous reaction functions in rows; B matrix for $u_t = (Com_t, Fin_t, Int_t, \Delta FX_t)'$ corresponding to the ordering of the ω_i in Table 3 with Standard errors in parentheses, where Com_t are net positions of order flows from the real economy, Fin_t are net positions in order flows of the financial economy, Int_t are interventions all denominated in million U.S. dollar. Net positions are calculated as buying minus selling positions and thus a positive (negative) sign reflects an excess demand (supply) for foreign currency. Similarly, a positive (negative) intervention sign reflects an excess demand (supply) for foreign currency. ΔFX_t is the log return of the Brazilian real per unit U.S. dollar FX rate. Columns 1 to 4 represent instantaneous responses to a positive unit trade innovation in real economy, financial economy orders and interventions and price innovations, respectively in the first (high trade intensity) variance state. Period S_1: 11/05/2009 - 02/05/2012. $*$, $**$, $***$ indicate a level of significance of 10%, 5% and 1%, respectively.

Table 5b

Estimated instantaneous reaction functions; B matrix for $u_t = (Com_t, Fin_t, \Delta FX_t)'$ corresponding to the ordering of the ω_i in Table 3 with Standard errors in parentheses. Period S_2: 03/05/2012 - 23/01/2015.

$$\hat{B} = \begin{bmatrix} \underset{(26.918)}{230.169^{***}} & \underset{(31.160)}{85.931^{***}} & \underset{(35.200)}{41.262} \\ \underset{(25.472)}{-32.076} & \underset{(255.009)}{583.885^{**}} & \underset{(159.238)}{-726.982^{***}} \\ \underset{(0.025)}{0.107^{***}} & \underset{(0.174)}{0.779^{***}} & \underset{(0.210)}{0.467^{**}} \end{bmatrix}$$

Table 5b: Estimated instantaneous reaction functions in rows; B matrix for $u_t = (Com_t, Fin_t, \Delta FX_t)'$ corresponding to the ordering of the ω_i in Table 3 with Standard errors in parentheses, where Com_t are net positions of order flows from the real economy, Fin_t are net positions in order flows of the financial economy all denominated in million U.S. dollar. Net positions are calculated as buying minus selling positions and thus a positive (negative) sign reflects an excess demand (supply) for foreign currency. ΔFX_t is the log return of the Brazilian real per unit U.S. dollar FX rate. Columns 1 to 3 represent instantaneous responses to a positive unit trade innovation in real economy, financial economy orders and price innovations, respectively in the first (low real economy; high financial economy trade intensity) variance state. Period S_2: 03/05/2012 - 23/01/2015. $*$, $**$, $***$ indicate a level of significance of 10%, 5% and 1%, respectively.

Table 6

Period S_1, h-step ahead Forecast error variance decompositions for FX returns (in %) for state 1

h	**Com**	**Fin**	**Int**	**FX returns**
1	7.309 (1.446)	0.911 (0.456)	0.114 (0.093)	91.666 (1.532)
2	10.224 (1.428)	0.900 (0.421)	1.445 (0.128)	87.431 (1.510)
3	10.144 (1.417)	0.951 (0.413)	1.970 (0.141)	86.936 (1.500)
4	10.176 (1.413)	0.950 (0.411)	2.207 (0.147)	86.667 (1.497)
5	10.169 (1.412)	0.950 (0.410)	2.290 (0.149)	86.591 (1.496)
10	10.164 (1.411)	0.949 (0.410)	2.345 (0.150)	86.542 (1.496)
20	10.164 (1.411)	0.949 (0.410)	2.346 (0.150)	86.541 (1.496)

Table 6: Period S_1 11/05/2009 - 02/05/2012, h-trading days ahead Forecast error variance decompositions for FX returns (in %) for state 1 (high trading intensity state). Columns 2 - 5 represent % variation of FX return innovations explained by a unit shock in order innovations from the real economy **Com**, from the financial economy **Fin** and intervention innovations **Int** as well as (own) return innovations **FX returns**, respectively. Numbers in brackets represent standard errors from 1000 bootstrap replications.

Table 7

Period S_1, h-step ahead Forecast error variance decompositions for financial economy OF (in %) for state 1

h	**Com**	**Fin**	**Int**	**FX returns**
1	1.182 (0.494)	95.487 (0.653)	3.323 (0.436)	0.008 (0.015)
2	1.438 (0.501)	92.272 (0.687)	6.209 (0.473)	0.081 (0.012)
3	1.542 (0.501)	90.330 (0.702)	7.936 (0.492)	0.192 (0.013)
4	1.572 (0.499)	89.662 (0.705)	8.558 (0.497)	0.207 (0.013)
5	1.576 (0.499)	89.398 (0.706)	8.813 (0.499)	0.213 (0.014)
10	1.576 (0.498)	89.241 (0.706)	8.967 (0.500)	0.215 (0.014)
20	1.576 (0.498)	89.240 (0.706)	8.968 (0.500)	0.215 (0.014)

Table 7: Period S_1 11/05/2009 - 02/05/2012, h-trading days ahead Forecast error variance decompositions for financial economy order flows (in %) for state 1 (high trading intensity state). Columns 2 - 5 represent % variation of financial economy order innovations explained by a unit shock in order innovations from the real economy **Com**, from (own) financial economy **Fin** and intervention innovations **Int** as well as return innovations **FX returns**, respectively. Numbers in brackets represent standard errors from 1000 bootstrap replications.

Table 8

Period S_1, h-step ahead Forecast error variance decompositions for real economy OF (in %) for state 1

h	**Com**	**Fin**	**Int**	**FX returns**
1	95.263 (0.558)	0.029 (0.180)	0.807 (0.187)	3.900 (0.523)
2	95.110 (0.554)	0.030 (0.180)	1.058 (0.203)	3.803 (0.515)
3	94.616 (0.565)	0.039 (0.175)	1.365 (0.217)	3.980 (0.524)
4	94.468 (0.566)	0.040 (0.174)	1.507 (0.221)	3.985 (0.524)
5	94.391 (0.567)	0.041 (0.174)	1.580 (0.222)	3.989 (0.524)
10	94.337 (0.567)	0.041 (0.174)	1.634 (0.223)	3.988 (0.524)
20	94.337 (0.567)	0.041 (0.174)	1.635 (0.223)	3.988 (0.524)

Table 8: Period S_1 11/05/2009 - 02/05/2012, h-trading days ahead Forecast error variance decompositions for real economy order flows (in %) for state 1 (high trading intensity state). Columns 2 - 5 represent % variation of real economy order innovations explained by a unit shock in order innovations from (own) real economy **Com**, from the financial economy **Fin** and intervention innovations **Int** as well as return innovations **FX returns**, respectively. Numbers in brackets represent standard errors from 1000 bootstrap replications.

Table 9

Period S_1, h-step ahead Forecast error variance decompositions for BCB interventions (in %) for state 1

h	**Com**	**Fin**	**Int**	**FX returns**
1	0.003 (0.003)	0.048 (0.024)	99.950 (0.024)	0.000 (0.000)
2	0.011 (0.004)	0.042 (0.022)	99.941 (0.023)	0.006 (0.001)
3	0.011 (0.005)	0.104 (0.014)	99.859 (0.015)	0.026 (0.002)
4	0.013 (0.005)	0.120 (0.012)	99.835 (0.013)	0.032 (0.003)
5	0.014 (0.005)	0.130 (0.011)	99.821 (0.012)	0.035 (0.003)
10	0.014 (0.005)	0.136 (0.011)	99.812 (0.012)	0.038 (0.003)
20	0.014 (0.005)	0.136 (0.011)	99.812 (0.012)	0.038 (0.003)

Table 9: Period S_1 11/05/2009 - 02/05/2012, h-trading days ahead Forecast error variance decompositions for interventions (in %) for state 1 (high trading intensity state). Columns 2 - 5 represent % variation of real economy order innovations explained by a unit shock in order innovations from the real economy **Com**, from the financial economy **Fin** and (own) intervention innovations **Int** as well as return innovations **FX returns**, respectively. Numbers in brackets represent standard errors from 1000 bootstrap replications.

Table 10

Period S_2, h-step ahead Forecast error variance decompositions for FX returns (in %)

State 1: column 2 - 4. State 2: column 5 - 7.

	State 1			State 2		
h	**Com**	**Fin**	**FX returns**	**Com**	**Fin**	**FX returns**
1	1.368 (0.169)	72.562 (5.404)	26.070 (5.358)	14.429 (1.338)	54.878 (5.418)	30.693 (5.558)
2	1.760 (0.186)	72.304 (5.386)	25.936 (5.331)	17.894 (1.267)	52.687 (5.149)	29.419 (5.350)
3	1.758 (0.185)	72.104 (5.312)	26.138 (5.257)	17.861 (1.261)	52.508 (5.070)	29.631 (5.270)
4	1.772 (0.186)	72.075 (5.311)	26.153 (5.255)	17.978 (1.261)	52.415 (5.060)	29.607 (5.262)
5	1.773 (0.186)	72.074 (5.310)	26.153 (5.255)	17.987 (1.260)	52.409 (5.059)	29.604 (5.261)
10	1.774 (0.186)	72.073 (5.310)	26.153 (5.255)	17.992 (1.260)	52.406 (5.058)	29.603 (5.261)
20	1.774 (0.186)	72.073 (5.310)	26.153 (5.255)	17.992 (1.260)	52.406 (5.058)	29.603 (5.261)

Table 10: Period S_2 03/05/2012 - 23/01/2015, h-trading days ahead Forecast error variance decompositions for FX returns (in %) for state 1 (low real economy; high financial economy trade intensity) in column 2 - 4 and state 2 (high real economy; low financial economy trade intensity) in column 5 - 7. Columns 2 and 5 represent % variation of FX return innovations explained by a unit shock in order innovations from the real economy **Com**, columns 3 and 6 from financial economy innovations **Fin**, column 4 and 7 (own) FX return innovations **FX returns** in state 1 and 2, respectively. Numbers in brackets represent standard errors from 1000 bootstrap replications.

Table 11

Period S_2, h-step ahead Forecast error variance decompositions for financial economy OF (in %), State 1: column 2 - 4. State 2: column 5 - 7.

	State 1			State 2		
h	**Com**	**Fin**	**FX returns**	**Com**	**Fin**	**FX returns**
1	0.118 (0.044)	39.166 (6.411)	60.716 (6.410)	1.218 (0.466)	28.941 (5.555)	69.841 (5.553)
2	0.117 (0.044)	38.705 (6.394)	61.178 (6.393)	1.202 (0.463)	28.550 (5.521)	70.249 (5.519)
3	0.116 (0.044)	38.800 (6.391)	61.084 (6.390)	1.199 (0.462)	28.632 (5.523)	70.169 (5.521)
4	0.117 (0.044)	38.804 (6.391)	61.079 (6.390)	1.202 (0.462)	28.635 (5.523)	70.163 (5.521)
5	0.117 (0.044)	38.804 (6.391)	61.079 (6.390)	1.202 (0.462)	28.635 (5.523)	70.163 (5.521)
10	0.117 (0.044)	38.804 (6.391)	61.079 (6.390)	1.202 (0.462)	28.635 (5.523)	70.163 (5.521)
20	0.117 (0.044)	38.804 (6.391)	61.079 (6.390)	1.202 (0.462)	28.635 (5.523)	70.163 (5.521)

Table 11: Period S_2 03/05/2012 - 23/01/2015, h-trading days ahead Forecast error variance decompositions for financial economy order flows (in %) for state 1 (low real economy; high financial economy trade intensity) in column 2 - 4 and state 2 (high real economy; low financial economy trade intensity) in column 5 - 7. Columns 2 and 5 represent % variation in financial economy order flow innovations explained by a unit shock in order innovations from the real economy **Com**, columns 3 and 6 from (own) financial economy innovations **Fin**, column 4 and 7 FX return innovations **FX returns** in state 1 and 2, respectively. Numbers in brackets represent standard errors from 1000 bootstrap replications.

Table 12

Period S_2, h-step ahead Forecast error variance decompositions for real economy OF (in %)

State 1: column 2 - 4. State 2: column 5 - 7.

	State 1			State 2		
h	**Com**	**Fin**	**FX returns**	**Com**	**Fin**	**FX returns**
1	85.359	11.898	2.743	98.660	0.986	0.354
	(2.175)	(2.124)	(1.054)	(0.202)	(0.163)	(0.137)
2	81.019	14.855	4.126	98.152	1.290	0.558
	(2.012)	(1.732)	(0.950)	(0.199)	(0.133)	(0.131)
3	80.204	14.504	5.292	98.008	1.271	0.722
	(2.043)	(1.735)	(1.024)	(0.208)	(0.135)	(0.144)
4	80.115	14.493	5.392	97.993	1.271	0.736
	(2.039)	(1.719)	(1.027)	(0.208)	(0.134)	(0.145)
5	80.076	14.471	5.453	97.986	1.269	0.745
	(2.038)	(1.715)	(1.029)	(0.208)	(0.133)	(0.145)
10	80.067	14.466	5.466	97.984	1.269	0.746
	(2.038)	(1.714)	(1.030)	(0.208)	(0.133)	(0.145)
20	80.067	14.466	5.466	97.984	1.269	0.746
	(2.038)	(1.714)	(1.030)	(0.208)	(0.133)	(0.145)

Table 12: Period S_2 03/05/2012 - 23/01/2015, h-trading days ahead Forecast error variance decompositions for real economy order flows (in %) for state 1 (low real economy; high financial economy trade intensity) in column 2 - 4 and state 2 (high real economy; low financial economy trade intensity) in column 5 - 7. Columns 2 and 5 represent % variation in real economy order flow innovations explained by a unit shock in order innovations from (own) real economy **Com**, columns 3 and 6 from financial economy innovations **Fin**, column 4 and 7 FX return innovations **FX returns** in state 1 and 2, respectively. Numbers in brackets represent standard errors from 1000 bootstrap replications.

Appendix C: A decomposition procedure

Let Σ_1 and Σ_2 be two symmetric $(K \times K)$ Matrices, where Σ_1 is positive-definite then the following algorithm computes a non-singular matrix D, such that $D'\Sigma_1 D = I_K$ and $D'\Sigma_2 D = diag(\omega_1, ..., \omega_K) = \Omega$ (see Golub and van Loan 1989, p.469):

1) Compute Cholesky decomposition $\Sigma_1 = GG'$

2) Compute $C = G^{-1}\Sigma_2 G'^{-1}$

3) Compute Schur decomposition $Q'CQ = diag(\omega_1, ..., \omega_K)$

4) Compute $D = G^{-1}Q$.

If one substitutes $W = D'^{-1} = \boldsymbol{B}$, then $\Sigma_1 = WW'$ and $\Sigma_2 = W\Omega W'$ holds. The simultaneous decomposition is unique, iff Elements $diag(\Omega)$ are unique. As a result one obtains instantantaneous responses in $\boldsymbol{B}$ scaled to a unit shock in variance regime 1 and corresponding shifts in structural variances summarized in Ω.

3.9 Internet Appendix

Internet Appendix: FX pricing and strategic trading

This internet appendix provides additional results and robustness checks.

Additional results for the baseline model

- Table IA.I: Period S_1, h-step ahead Forecast error variance decompositions for FX returns (in %) for state 2
- Table IA.II: Period S_1, h-step ahead Forecast error variance decompositions for financial economy OF (in %) for state 2
- Table IA.III: Period S_1, h-step ahead Forecast error variance decompositions for real economy OF (in %) for state 2
- Table IA.IV: Period S_1, h-step ahead Forecast error variance decompositions for BCB interventions (in %) for state 2
- Table IA.V: Reduced form VAR estimates of the baseline specification in subsample S_1 and S_2

Robustness check results: Baseline model excluding interventions in subsample 1

- Table IA.VI Estimate of mixture probabilities
- Table IA.VII Estimate of structural variances
- Table IA.VIII Tests for equality of structural variances
- Table IA.IX Estimated $\boldsymbol{B}$–Matrix
- Table IA.X: Period S_1, h-step ahead Forecast error variance decompositions for FX returns (in %)
- Table IA.XI: Period S_1, h-step ahead Forecast error variance decompositions for financial economy OF (in %)
- Table IA.XII: Period S_1, h-step ahead Forecast error variance decompositions for real economy OF (in %)

Robustness check results: Baseline model excluding order flows in subsample 1

- Table IA.XIII Estimate of mixture probabilities
- Table IA.XIV Estimate of structural variances
- Table IA.XV Tests for equality of structural variances
- Table IA.XVI Estimated $\boldsymbol{B}$–Matrix
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Table IA.I

Period S_1, h-step ahead Forecast error variance decompositions for FX returns (in %) for state 2

h	**Com**	**Fin**	**Int**	**FX returns**
1	2.201 (0.443)	0.131 (0.062)	0.001 (0.001)	97.667 (0.452)
2	3.195 (0.460)	0.134 (0.060)	0.014 (0.002)	96.657 (0.469)
3	3.188 (0.459)	0.143 (0.059)	0.019 (0.002)	96.651 (0.468)
4	3.207 (0.459)	0.143 (0.059)	0.021 (0.002)	96.629 (0.469)
5	3.207 (0.459)	0.143 (0.059)	0.022 (0.002)	96.627 (0.469)
10	3.208 (0.459)	0.143 (0.059)	0.023 (0.002)	96.626 (0.469)
20	3.208 (0.459)	0.143 (0.059)	0.023 (0.002)	96.626 (0.469)

Table IA.I: Period S_1 11/05/2009 - 02/05/2012, h-trading days ahead Forecast error variance decompositions for FX returns (in %) for state 2 (low trading intensity state). Columns 2 - 5 represent % variation of FX return innovations explained by a unit shock in order innovations from the real economy **Com**, from the financial economy **Fin** and intervention innovations **Int** as well as (own) return innovations **FX returns**, respectively. Numbers in brackets represent standard errors from 1000 bootstrap replications.

Table IA.II

Period S_1, h-step ahead Forecast error variance decompositions for financial economy OF (in %) for state 2

h	**Com**	**Fin**	**Int**	**FX returns**
1	2.517	97.208	0.216	0.059
	(1.053)	(1.068)	(0.033)	(0.118)
2	3.125	95.844	0.411	0.620
	(1.087)	(1.091)	(0.044)	(0.092)
3	3.379	94.605	0.530	1.487
	(1.093)	(1.090)	(0.052)	(0.102)
4	3.460	94.351	0.574	1.615
	(1.094)	(1.090)	(0.055)	(0.107)
5	3.475	94.268	0.592	1.665
	(1.094)	(1.090)	(0.056)	(0.108)
10	3.481	94.232	0.604	1.683
	(1.094)	(1.090)	(0.057)	(0.109)
20	3.481	94.232	0.604	1.683
	(1.094)	(1.090)	(0.057)	(0.109)

Table IA.II: Period S_1 11/05/2009 - 02/05/2012, h-trading days ahead Forecast error variance decompositions for financial economy order flows (in %) for state 2 (low trading intensity state). Columns 2 - 5 represent % variation of financial economy order innovations explained by a unit shock in order innovations from the real economy **Com**, from (own) financial economy **Fin** and intervention innovations **Int** as well as return innovations **FX returns**, respectively. Numbers in brackets represent standard errors from 1000 bootstrap replications.

Table IA.III

Period S_1, h-step ahead Forecast error variance decompositions for real economy OF (in %) for state 2

h	**Com**	**Fin**	**Int**	**FX returns**
1	87.317	0.013	0.023	12.647
	(1.496)	(0.078)	(0.006)	(1.494)
2	87.571	0.013	0.030	12.387
	(1.481)	(0.078)	(0.006)	(1.479)
3	86.999	0.017	0.038	12.946
	(1.497)	(0.076)	(0.007)	(1.496)
4	86.961	0.018	0.042	12.979
	(1.499)	(0.076)	(0.007)	(1.497)
5	86.940	0.018	0.044	12.998
	(1.499)	(0.076)	(0.008)	(1.497)
10	86.935	0.018	0.046	13.001
	(1.499)	(0.076)	(0.008)	(1.498)
20	86.935	0.018	0.046	13.001
	(1.499)	(0.076)	(0.008)	(1.498)

Table IA.III: Period S_1 11/05/2009 - 02/05/2012, h-trading days ahead Forecast error variance decompositions for real economy order flows (in %) for state 2 (low trading intensity state). Columns 2 - 5 represent % variation of real economy order innovations explained by a unit shock in order innovations from (own) real economy **Com**, from the financial economy **Fin** and intervention innovations **Int** as well as return innovations **FX returns**, respectively. Numbers in brackets represent standard errors from 1000 bootstrap replications.

Table IA.IV

Period S_1, h-step ahead Forecast error variance decompositions for BCB interventions (in %) for state 2

h	**Com**	**Fin**	**Int**	**FX returns**
1	0.083 (0.101)	0.743 (0.383)	99.165 (0.404)	0.009 (0.054)
2	0.356 (0.147)	0.655 (0.347)	98.318 (0.411)	0.671 (0.171)
3	0.349 (0.148)	1.562 (0.231)	95.251 (0.579)	2.839 (0.454)
4	0.415 (0.159)	1.771 (0.213)	94.324 (0.666)	3.489 (0.538)
5	0.427 (0.161)	1.913 (0.209)	93.795 (0.716)	3.865 (0.584)
10	0.443 (0.164)	1.998 (0.207)	93.449 (0.749)	4.109 (0.613)
20	0.444 (0.164)	1.999 (0.207)	93.446 (0.749)	4.112 (0.613)

Table IA.IV: Period S_1 11/05/2009 - 02/05/2012, h-trading days ahead. Forecast error variance decompositions for interventions (in %) for state 2 (low trading intensity state). Columns 2 - 5 represent % variation of real economy order innovations explained by a unit shock in order innovations from the real economy **Com**, from the financial economy **Fin** and (own) intervention innovations **Int** as well as return innovations **FX returns**, respectively. Numbers in brackets represent standard errors from 1000 bootstrap replications.

Table AI.V

Reduced form VAR estimates of the baseline specification in subsample S_1 and S_2.

	Baseline model in S_1				Baseline model in S_2		
Parameter	**Com**	**Fin**	**Int**	**FX returns**	**Com**	**Fin**	**FX returns**
ν	30.179^{*}	-42.043^{*}	16.845^{***}	-0.058^{*}	-33.331^{**}	-36.877^{*}	0.042^{**}
	(16.433)	(22.815)	(3.762)	(0.035)	(13.088)	(20.462)	(0.021)
Com_{t-1}	0.245^{***}	-0.071	-0.005	$2.651\times10^{4\,***}$	0.186^{***}	0.019	$2.535\times10^{4\,***}$
	(0.039)	(0.055)	(0.008)	(8.152×10^{5})	(0.034)	(0.051)	(6.904×10^{5})
Fin_{t-1}	0.001	0.117^{***}	0.004	-0.000	-0.061^{***}	0.196^{***}	-0.000
	(0.020)	(0.030)	(0.004)	(0.000)	(0.022)	(0.034)	(0.000)
Int_{t-1}	0.035	0.308^{***}	0.371^{***}	0.000			
	(0.063)	(0.104)	(0.028)	(0.000)			
FX_{t-1}	-8.883	-28.024	-4.731	0.021	-40.725^{**}	-29.214	-0.071^{*}
	(20.012)	(26.902)	(3.701)	(0.043)	(19.763)	(36.494)	(0.038)
Com_{t-2}	0.097^{***}	-0.006	0.012	-0.000	0.145^{***}	-0.004	-0.000
	(0.036)	(0.052)	(0.008)	(0.000)	(0.033)	(0.048)	(0.000)
Fin_{t-2}	-0.009	0.058^{**}	0.017^{***}	-0.000	-0.000	0.008	-0.000
	(0.018)	(0.028)	(0.005)	(0.000)	(0.021)	(0.037)	(0.000)
Int_{t-2}	0.030	0.109	0.137^{***}	0.000			
	(0.063)	(0.097)	(0.024)	(0.000)			
FX_{t-2}	21.234	-36.830	-10.095^{***}	0.054	17.994	24.608	-0.001
	(17.846)	(24.618)	(3.427)	(0.040)	(19.855)	(31.693)	(0.033)
$\Delta SELIC_{t-1}$	85.237	-16.211	14.712	-0.182	264.843	378.684	0.137
	(146.710)	(199.462)	(27.788)	(0.313)	(188.124)	(260.666)	(0.270)
ΔVIX_{t-1}	5.380	6.486	6.558^{**}	0.078^{***}	-17.429	20.556	0.055^{*}
	(13.624)	(18.811)	(2.652)	(0.027)	(17.428)	(27.381)	(0.029)
ΔCI_{t-1}	0.892	8.251	-0.752	0.005	3.782	13.216	-0.003
	(6.022)	(8.684)	(1.366)	(0.012)	(8.706)	(13.385)	(0.013)
$\Delta EMBI_{t-1}$	-6.332	-3.948	1.077	-0.004	-5.624	4.315	-0.023^{***}
	(4.925)	(7.212)	(1.079)	(0.010)	(3.518)	(5.572)	(0.006)

Table AI.V: Reduced form VAR estimates of the baseline specification in subsample S_1 and S_2 on the left and right hand side, respectively. **Com**, **Fin**, **Int** and **FX returns** are equations corresponding to net positions in commercial and financial orders, interventions (all in million US Dollar) and FX log returns (in %). $\Delta SELIC$, ΔVIX, ΔCI and $\Delta EMBI$ denote first differences of the annualized SELIC base rate (domestic interest), the Chicago Board of Equities volatility index, the Commodity Research Bureau's commodity price index and the JP Morgan EMBI Spread for Brazil. ν denotes a constant. Numbers in brackets represent heteroscedasticity consistent standard errors from the inverse of the hessian of the log-likelihood function. $*$, $**$, $***$ indicate a level of significance of 10 %, 5 % and 1 %, respectively.

Table AI.VI

Estimates of state probabilities γ_m for S_1

with number of states $M = 3$ and lag order $p = 2$.

Parameters	**Estimate**	**Std-Dev.**
γ_1	0.159	0.042
γ_2	0.776	0.044
$\gamma_3 = 1-\gamma_1-\gamma_2$	0.066	-

Table AI.VI: Estimates of state probabilities γ_m for states $i = 1, ..., M$. S_1 denotes period 11/05/2009 to 02/05/2012 with number of states $M = 3$ and lag order $p = 2$, where M and p are kept constant for reasons of comparability. **Estimate**, **Std-Dev.** is the parameter estimate and corresponding standard deviation, respectively.

Table AI.VII

Estimates of structural variances ω_i corresponding to $u_t = (Com_t, Fin_t, \Delta FX_t)'$ in S_1

Parameters	**Estimate**	**Std.-dev**
ω_1	0.149	0.028
ω_2	0.454	0.103
ω_3	-	-
ω_4	0.231	0.046

Table AI.VII: Estimates of structural variances ω_i for $i = 1, ..., K$ endogeneous variables corresponding to $u_t = (Com_t, Fin_t, \Delta FX_t)'$ for period 11/05/2009 to 02/05/2012 denoted S_1. **Estimate**, **Std-Dev.** is the parameter estimate and corresponding standard deviation, respectively.

Table AI.VIII

Wald tests for equality of ω_i from Table IA.VII

H_0	**test statistic**	**p-value**
$\omega_1 = \omega_2$	8.659	0.003
$\omega_1 = \omega_4$	2.103	0.147
$\omega_2 = \omega_4$	3.581	0.058

Table AI.VIII: Wald test results for a equal change in structural variances from Table IA.VII. H_0 : $\omega_i = \omega_j$ for all $i \neq j$ is the Null of pairwise-equality of state two variances. S_1 denotes results for the period 11/05/2009 to 02/05/2012. **test statistic**, **p-value** are the corresponding test statistic and p-value, respectively.

Table AI.IX

Estimated instantaneous reaction functions; B matrix for $u_t = (Com_t, Fin_t, \Delta FX_t)'$ corresponding to the ordering of the ω_i in Table IA.VII with Standard errors in parentheses. Period S_1: 11/05/2009 to 02/05/2012.

$$\hat{B} = \begin{bmatrix} \underset{(248.897)}{556.26}^{**} & \underset{(68.721)}{82.408} & \underset{(259.164)}{372.813} \\ \underset{(121.896)}{-276.913}^{**} & \underset{(63.423)}{590.222}^{***} & \underset{(195.072)}{-129.792} \\ \underset{(0.743)}{-0.362} & \underset{(0.200)}{0.145} & \underset{(0.177)}{1.225}^{***} \end{bmatrix}$$

Table IX: Estimated instantaneous reaction functions in rows; B matrix for $u_t = (Com_t, Fin_t, \Delta FX_t)'$ corresponding to the ordering of the ω_i in Table IA.VII with Standard errors in parentheses, where Com_t are net positions of order flows from the real economy, Fin_t are net positions in order flows of the financial economy all denominated in Mill US Dollar. Net positions are calculated as buying minus selling positions and thus a positive (negative) sign reflects an excess demand (supply) for foreign currency. ΔFX_t is the log return of the Brazilian Real per unit US Dollar FX rate. Columns 1 to 3 represent instantaneous responses to a positive unit trade innovation in real economy, financial economy orders and price innovations, respectively in the first (high trade intensity) variance state. Period S_1: 11/05/2009 to 02/05/2012. $*$, $**$, $***$ indicate a level of significance of 10%, 5% and 1%, respectively.

Table IA.X

Period S_1, h-step ahead Forecast error variance decompositions for FX returns (in %) for state 1 (column 2 - 4) and state 2 (column 5 - 7).

	State 1			State 2		
h	**Com**	**Fin**	**FX returns**	**Com**	**Fin**	**FX returns**
1	7.951 (2.077)	1.269 (0.578)	90.780 (2.167)	5.224 (1.410)	2.535 (1.086)	92.242 (1.828)
2	9.265 (1.836)	1.255 (0.569)	89.480 (1.937)	6.117 (1.290)	2.520 (1.077)	91.364 (1.730)
3	9.337 (1.836)	1.259 (0.568)	89.404 (1.936)	6.166 (1.291)	2.528 (1.075)	91.306 (1.730)
4	9.341 (1.834)	1.259 (0.568)	89.400 (1.934)	6.168 (1.290)	2.528 (1.075)	91.304 (1.729)
5	9.341 (1.834)	1.259 (0.568)	89.400 (1.934)	6.168 (1.290)	2.528 (1.075)	91.303 (1.729)
10	9.341 (1.834)	1.259 (0.568)	89.400 (1.934)	6.168 (1.290)	2.528 (1.075)	91.303 (1.729)
20	9.341 (1.834)	1.259 (0.568)	89.400 (1.934)	6.168 (1.290)	2.528 (1.075)	91.303 (1.729)

Table IA.X: Period S_1 11/05/2009 - 02/05/2012, h-trading days ahead Forecast error variance decompositions for FX returns (in %) for state 1 (high trade intensity) in column 2 - 4 and state 2 (low trade intensity) in column 5 - 7. Columns 2 and 5 represent % variation of FX return innovations explained by a unit shock in order innovations from the real economy **Com**, columns 3 and 6 from financial economy innovations **Fin**, column 4 and 7 (own) FX return innovations **FX returns** in state 1 and 2, respectively. Numbers in brackets represent standard errors from 1000 bootstrap replications.

Table IA.XI

Period S_1, h-step ahead Forecast error variance decompositions

for financial economy OF (in %) for state 1 (column 2 - 4) and state 2 (column 5 - 7).

	State 1			State 2		
h	**Com**	**Fin**	**FX returns**	**Com**	**Fin**	**FX returns**
1	17.353 (2.502)	78.835 (2.606)	3.812 (1.317)	6.600 (1.236)	91.157 (1.393)	2.243 (0.809)
2	17.808 (2.514)	77.660 (2.617)	4.532 (1.404)	6.826 (1.255)	90.488 (1.431)	2.686 (0.864)
3	17.555 (2.502)	76.828 (2.612)	5.617 (1.484)	6.757 (1.249)	89.899 (1.452)	3.344 (0.909)
4	17.581 (2.502)	76.658 (2.610)	5.761 (1.495)	6.774 (1.250)	89.793 (1.456)	3.433 (0.915)
5	17.577 (2.501)	76.633 (2.610)	5.791 (1.497)	6.773 (1.250)	89.776 (1.456)	3.451 (0.916)
10	17.577 (2.501)	76.625 (2.610)	5.798 (1.497)	6.774 (1.250)	89.771 (1.456)	3.456 (0.917)
20	17.577 (2.501)	76.625 (2.610)	5.798 (1.497)	6.774 (1.250)	89.771 (1.456)	3.456 (0.917)

Table IA.XI: Period S_1 11/05/2009 - 02/05/2012, h-trading days ahead Forecast error variance decompositions for financial economy order flows (in %) for state 1 (high trade intensity) in column 2 - 4 and state 2 (low trade intensity) in column 5 - 7. Columns 2 and 5 represent % variation in financial economy order flow innovations explained by a unit shock in order innovations from the real economy **Com**, columns 3 and 6 from (own) financial economy innovations **Fin**, column 4 and 7 FX return innovations **FX returns** in state 1 and 2, respectively. Numbers in brackets represent standard errors from 1000 bootstrap replications.

Table IA.XII

Period S_1, h-step ahead Forecast error variance decompositions for real economy OF (in %) for state 1 (column 2 - 4) and state 2 (column 5 - 7).

	State 1			State 2		
h	**Com**	**Fin**	**FX returns**	**Com**	**Fin**	**FX returns**
1	67.975	1.492	30.533	56.773	3.788	39.439
	(4.026)	(0.530)	(3.965)	(4.312)	(1.272)	(4.219)
2	68.828	1.518	29.654	57.691	3.868	38.441
	(3.958)	(0.531)	(3.896)	(4.276)	(1.277)	(4.176)
3	68.788	1.491	29.721	57.666	3.801	38.533
	(3.962)	(0.525)	(3.900)	(4.278)	(1.265)	(4.180)
4	68.814	1.487	29.699	57.699	3.790	38.512
	(3.960)	(0.524)	(3.899)	(4.278)	(1.263)	(4.179)
5	68.815	1.485	29.700	57.700	3.786	38.514
	(3.960)	(0.524)	(3.899)	(4.278)	(1.262)	(4.179)
10	68.815	1.485	29.701	57.701	3.784	38.515
	(3.960)	(0.524)	(3.899)	(4.278)	(1.262)	(4.179)
20	68.815	1.485	29.701	57.701	3.784	38.515
	(3.960)	(0.524)	(3.899)	(4.278)	(1.262)	(4.179)

Table IA.XII: Period S_1 11/05/2009 - 02/05/2012, h-trading days ahead Forecast error variance decompositions for real economy order flows (in %) for state 1 (high trade intensity) in column 2 - 4 and state 2 (low trade intensity) in column 5 - 7. Columns 2 and 5 represent % variation in real economy order flow innovations explained by a unit shock in order innovations from (own) real economy **Com**, columns 3 and 6 from financial economy innovations **Fin**, column 4 and 7 FX return innovations **FX returns** in state 1 and 2, respectively. Numbers in brackets represent standard errors from 1000 bootstrap replications.

Table IA.XIII

Estimates of state probabilities γ_m for S_1 with number of states $M = 2$ and lag order $p = 2$.

Parameters	**Estimate**	**Std-Dev.**
γ_1	0.438	0.030
$\gamma_2 = 1 - \gamma_1$	0.563	-

Table IA.XIII: Estimates of state probabilities γ_m for states $i = 1, ..., M$. S_1 denotes period 11/05/2009 to 02/05/2012 with number of states $M = 2$ and lag order $p = 2$, where number of states $M = 2$ deviates from the baseline model, because of singularity issues, which we see as evidence for no outliers in interventions and FX returns. **Estimate**, **Std-Dev.** is the parameter estimate and corresponding standard deviation, respectively.

Table IA.XIV

Estimates of structural variances ω_i corresponding to $u_t = (Int_t, \Delta FX_t)'$ in S_1

Parameters	**Estimate**	**Std.-dev**
ω_1	-	-
ω_2	-	-
ω_3	0.013	0.002
ω_4	3.077	0.039

Table IA.XIV: Estimates of structural variances ω_i for $i = 1, ..., K$ endogeneous variables corresponding to $u_t = (Int_t, \Delta FX_t)'$ for period 11/05/2009 to 02/05/2012 denoted S_1. **Estimate**, **Std-Dev.** is the parameter estimate and corresponding standard deviation, respectively.

Table IA.XV

Wald tests for equality of ω_i from Table IA.XIV

H_0	**test statistic**	**p-value**
$\omega_1 = \omega_2$	-	-
$\omega_1 = \omega_3$	-	-
$\omega_1 = \omega_4$	-	-
$\omega_2 = \omega_3$	-	-
$\omega_2 = \omega_4$	-	-
$\omega_3 = \omega_4$	68.986	0.000

Table IA.XV: Wald test results for a equal change in structural variances from Table IA.XIV. $H_0: \quad \omega_i = \omega_j$ for all $i \neq j$ is the Null of pairwise-equality of state two variances. S_1 denotes results for the period 11/05/2009 to 02/05/2012. **test statistic**, **p-value** are the corresponding test statistic and p-value, respectively.

Table IA.XVI

Estimated instantaneous reaction functions; B matrix for $u_t = (Int_t, \Delta FX_t)'$ corresponding to the ordering of the ω_i in Table IA.XIV with Standard errors in parentheses. Period S_1: 11/05/2009 - 02/05/2012.

$$\hat{B} = \begin{bmatrix} \underset{(14.750)}{316.665^{***}} & \underset{(1.121)}{-0.023} \\ \underset{(0.033)}{0.011} & \underset{(0.024)}{0.520^{***}} \end{bmatrix}$$

Table IA.XVI: Estimated instantaneous reaction functions in rows; B matrix for $u_t = (Int_t, \Delta FX_t)'$ corresponding to the ordering of the ω_i in Table IA.XIV with Standard errors in parentheses, where Com_t are net positions of order flows from the real economy, Fin_t are net positions in order flows of the financial economy, Int_t are interventions all denominated in Mill US Dollar. A positive (negative) intervention sign reflects an excess demand (supply) for foreign currency. ΔFX_t is the log return of the Brazilian Real per unit US Dollar FX rate. Columns 1 and 2 represent instantaneous responses to a positive unit intervention and price innovations, respectively in the first (high intervention; low FX return) variance state. Period S_1: 11/05/2009 - 02/05/2012. $*$, $**$, $***$ indicate a level of significance of 10%, 5% and 1%, respectively.

Table IA.XVII

Period S_1, h-step ahead Forecast error variance decompositions for FX returns (in %) for state 1 (column 2 - 3) and state 2 (column 4 - 5).

	State 1		State 2	
h	**Int**	**FX returns**	**Int**	**FX returns**
1	0.042 (0.039)	99.958 (0.039)	0.000 (0.000)	100.000 (0.000)
2	0.915 (0.058)	99.085 (0.058)	0.004 (0.000)	99.996 (0.000)
3	1.448 (0.071)	98.552 (0.071)	0.006 (0.001)	99.994 (0.001)
4	1.661 (0.076)	98.339 (0.076)	0.007 (0.001)	99.993 (0.001)
5	1.749 (0.078)	98.251 (0.078)	0.008 (0.001)	99.992 (0.001)
10	1.801 (0.080)	98.199 (0.080)	0.008 (0.001)	99.992 (0.001)
20	1.802 (0.080)	98.198 (0.080)	0.008 (0.001)	99.992 (0.001)

Table IA.XVII: Period S_1 11/05/2009 - 02/05/2012, h-trading days ahead Forecast error variance decompositions for FX returns (in %) for state 1 (high trade; intervention intensity) in column 2 - 3 and state 2 (low trade; intervention intensity) in column 4 - 5. Columns 2 and 4 represent % variation of FX return innovations explained by a unit shock in interventions **Int** and column 3 and 5 (own) FX return innovations **FX returns** in state 1 and 2, respectively. Numbers in brackets represent standard errors from 1000 bootstrap replications.

Table IA.XVIII

Period S_1, h-step ahead Forecast error variance decompositions

for BCB interventions (in %) for state 1 (column 2 - 3) and state 2 (column 4 - 5).

	State 1		State 2	
h	**Int**	**FX returns**	**Int**	**FX returns**
1	100.000 (0.000)	0.000 (0.000)	100.000 (0.028)	0.000 (0.028)
2	99.998 (0.000)	0.002 (0.000)	99.464 (0.103)	0.536 (0.103)
3	99.986 (0.001)	0.014 (0.001)	96.825 (0.361)	3.175 (0.361)
4	99.983 (0.001)	0.017 (0.001)	96.242 (0.419)	3.758 (0.419)
5	99.982 (0.001)	0.018 (0.001)	95.929 (0.449)	4.071 (0.449)
10	99.981 (0.001)	0.019 (0.001)	95.758 (0.465)	4.242 (0.465)
20	99.981 (0.001)	0.019 (0.001)	95.757 (0.465)	4.243 (0.465)

Table IA.XVIII: Period S_1 11/05/2009 - 02/05/2012, h-trading days ahead Forecast error variance decompositions for interventions (in %) for state 1 (high trade; intervention intensity) in column 2 - 3 and state 2 (low trade; intervention intensity) in column 4 - 5. Columns 2 and 4 represent % variation in intervention innovations explained by a (own) unit shock **Int** and column 3 and 5 FX return innovations **FX returns** in state 1 and 2, respectively. Numbers in brackets represent standard errors from 1000 bootstrap replications.

Table IA.XIX

Estimates of state probabilities γ_m for S_1 and S_2

with number of states $M = 3$ and lag order $p = 2$.

	S_1		S_2	
Parameters	**Estimate**	**Std-Dev.**	**Estimate**	**Std-Dev.**
γ_1	0.345	0.038	0.247	0.052
γ_2	0.590	0.038	0.640	0.051
$\gamma_3 = 1-\gamma_1-\gamma_2$	0.066	-	0.113	-

Table IA.XIX: Estimates of state probabilities γ_m for states $i = 1, ..., M$. S_1 denotes period 11/05/2009 to 02/05/2012 and S_2 denotes the period 03/05/2012 to 23/01/2015 with number of states $M = 3$ and lag order $p = 2$, where M and p are kept constant for reasons of comparability. **Estimate**, **Std-Dev.** is the parameter estimate and corresponding standard deviation, respectively.

Table IA.XX

Estimates of structural variances ω_i corresponding to $u_t = (Com_t, Fin_t, Int_t, \Delta FX_t)'$ in S_1 and $u_t = (Com_t, Fin_t, \Delta FX_t)'$ in S_2

	S_1		S_2	
Parameters	**Estimate**	**Std.-dev**	**Estimate**	**Std.-dev**
ω_1	0.703	0.127	2.036	0.597
ω_2	0.325	0.053	0.142	0.024
ω_3	0.022	0.004	-	-
ω_4	2.514	0.362	0.233	0.041

Table IA.XX: Estimates of structural variances ω_i for $i = 1, ..., K$ endogeneous variables corresponding to $u_t = (Com_t, Fin_t, Int_t, \Delta FX_t)'$ for period 11/05/2009 to 02/05/2012 denoted S_1 and $u_t = (Com_t, Fin_t, \Delta FX_t)'$ for period 03/05/2012 to 23/01/2015 denoted S_2. **Estimate**, **Std-Dev.** is the parameter estimate and corresponding standard deviation, respectively.

Table IA.XXI

Wald tests for equality of ω_i from Table IA.XX

	S_1		S_2	
H_0	**test statistic**	**p-value**	**test statistic**	**p-value**
$\omega_1 = \omega_2$	7.490	0.006	10.106	0.002
$\omega_1 = \omega_3$	28.170	0.000	-	-
$\omega_1 = \omega_4$	24.000	0.000	9.220	0.002
$\omega_2 = \omega_3$	32.184	0.000	-	-
$\omega_2 = \omega_4$	35.873	0.000	3.625	0.057
$\omega_3 = \omega_4$	46.220	0.000	-	-

Table IA.XXI: Wald test results for a equal change in structural variances from Table IA.XX. $H_0: \quad \omega_i = \omega_j$ for all $i \neq j$ is the Null of pairwise-equality of state two variances. S_1 denotes results for the period 11/05/2009 to 02/05/2012 and S_2 for period 03/05/2012 to 23/01/2015, respectively. **test statistic**, **p-value** are the corresponding test statistic and p-value, respectively.

Table XXII

Estimated instantaneous reaction functions; B matrix for $u_t = (Com_t, Fin_t, Int_t, \Delta FX_t)'$ corresponding to the ordering of the ω_i in Table IA.XX with Standard errors in parentheses. Period S_1: 11/05/2009 - 02/05/2012.

$$\hat{B} = \begin{bmatrix} \underset{(22.050)}{345.819^{***}} & \underset{(55.303)}{2.425} & \underset{(25.742)}{32.722} & \underset{(18.762)}{69.646^{***}} \\ \underset{(67.634)}{-66.421} & \underset{(37.953)}{647.141^{***}} & \underset{(49.704)}{122.460^{**}} & \underset{(18.288)}{7.764} \\ \underset{(4.147)}{-2.055} & \underset{(6.917)}{-8.317} & \underset{(20.985)}{345.044^{***}} & \underset{(1.812)}{-0.299} \\ \underset{(0.057)}{0.142^{**}} & \underset{(0.050)}{0.045} & \underset{(0.038)}{0.018} & \underset{(0.027)}{0.492^{***}} \end{bmatrix}$$

Table XXII: Estimated instantaneous reaction functions in rows; B matrix for $u_t = (Com_t, Fin_t, Int_t, \Delta FX_t)'$ corresponding to the ordering of the ω_i in Table IA.XX with Standard errors in parentheses, where Com_t are net positions of order flows from the real economy, Fin_t are net positions in order flows of the financial economy, Int_t are interventions all denominated in Mill US Dollar. Net positions are calculated as buying minus selling positions and thus a positive (negative) sign reflects an excess demand (supply) for foreign currency. Similarly, a positive (negative) intervention sign reflects an excess demand (supply) for foreign currency. ΔFX_t is the log return of the Brazilian Real per unit US Dollar FX rate. Columns 1 to 4 represent instantaneous responses to a positive unit trade innovation in real economy, financial economy orders and interventions and price innovations, respectively in the first (high trade intensity) variance state. Period S_1: 11/05/2009 - 02/05/2012. $*$, $**$, $***$ indicate a level of significance of 10%, 5% and 1%, respectively.

Table XXIII

Estimated instantaneous reaction functions; B matrix for $u_t = (Com_t, Fin_t, \Delta FX_t)'$ corresponding to the ordering of the ω_i in Table IA.XX with Standard errors in parentheses. Period S_2: 03/05/2012 - 23/01/2015.

$$\hat{B} = \begin{bmatrix} \underset{(29.950)}{227.23^{***}} & \underset{(33.094)}{78.072^{**}} & \underset{(35.998)}{41.813} \\ \underset{(26.487)}{-31.954} & \underset{(300.556)}{585.028^{*}} & \underset{(176.139)}{-733.196^{***}} \\ \underset{(0.026)}{0.111^{***}} & \underset{(0.192)}{0.786^{***}} & \underset{(0.236)}{0.461^{*}} \end{bmatrix}$$

Table XXIII: Estimated instantaneous reaction functions in rows; B matrix for $u_t = (Com_t, Fin_t, \Delta FX_t)'$ corresponding to the ordering of the ω_i in Table IA.XX with Standard errors in parentheses, where Com_t are net positions of order flows from the real economy, Fin_t are net positions in order flows of the financial economy all denominated in Mill US Dollar. Net positions are calculated as buying minus selling positions and thus a positive (negative) sign reflects an excess demand (supply) for foreign currency. ΔFX_t is the log return of the Brazilian Real per unit US Dollar FX rate. Columns 1 to 3 represent instantaneous responses to a positive unit trade innovation in real economy, financial economy orders and price innovations, respectively in the first (low real economy; high financial economy trade intensity) variance state. Period S_2: 03/05/2012 - 23/01/2015. $*$, $**$, $***$ indicate a level of significance of 10%, 5% and 1%, respectively.

Table IA.XXIV

Period S_1, h-step ahead Forecast error variance decompositions for FX returns (in %) for state 1 (column 2 - 5) and state 2 (column 6 - 9).

	State 1				State 2			
h	**Com**	**Fin**	**Int**	**FX returns**	**Com**	**Fin**	**Int**	**FX returns**
1	7.662	0.772	0.116	91.450	2.288	0.107	0.001	97.605
	(1.664)	(0.472)	(0.109)	(1.723)	(0.506)	(0.060)	(0.001)	(0.511)
2	10.547	0.779	1.482	87.191	3.269	0.112	0.014	96.605
	(1.638)	(0.432)	(0.151)	(1.699)	(0.526)	(0.057)	(0.002)	(0.531)
3	10.467	0.833	1.973	86.727	3.262	0.120	0.019	96.600
	(1.626)	(0.423)	(0.166)	(1.688)	(0.525)	(0.056)	(0.002)	(0.530)
4	10.499	0.834	2.200	86.466	3.281	0.120	0.021	96.578
	(1.622)	(0.421)	(0.172)	(1.685)	(0.525)	(0.056)	(0.003)	(0.531)
5	10.492	0.833	2.279	86.395	3.281	0.120	0.022	96.577
	(1.621)	(0.420)	(0.174)	(1.684)	(0.525)	(0.056)	(0.003)	(0.531)
10	10.488	0.833	2.330	86.349	3.281	0.120	0.022	96.576
	(1.620)	(0.420)	(0.176)	(1.683)	(0.525)	(0.056)	(0.003)	(0.531)
20	10.488	0.833	2.331	86.349	3.281	0.120	0.022	96.576
	(1.620)	(0.420)	(0.176)	(1.683)	(0.525)	(0.056)	(0.003)	(0.531)

Table IA.XXIV: Period S_1 11/05/2009 - 02/05/2012, h-trading days ahead Forecast error variance decompositions for FX returns (in %) for state 1 (high) and 2 (low trading intensity state). Columns 2 - 5 represent % variation of FX return innovations explained by a unit shock in order innovations from the real economy **Com**, from the financial economy **Fin** and intervention innovations **Int** as well as (own) return innovations **FX returns**, respectively. Numbers in brackets represent standard errors from 1000 bootstrap replications.

Table IA.XXV

Period S_1, h-step ahead Forecast error variance decompositions

for financial economy OF (in %) for state 1 (column 2 - 5) and state 2 (column 6 - 9).

	State 1				State 2			
h	**Com**	**Fin**	**Int**	**FX returns**	**Com**	**Fin**	**Int**	**FX returns**
1	1.007	95.558	3.422	0.014	2.221	97.438	0.233	0.108
	(0.530)	(0.725)	(0.506)	(0.021)	(1.139)	(1.166)	(0.039)	(0.169)
2	1.269	92.345	6.285	0.102	2.852	95.896	0.435	0.817
	(0.541)	(0.771)	(0.545)	(0.016)	(1.174)	(1.180)	(0.053)	(0.129)
3	1.401	90.504	7.902	0.193	3.173	94.712	0.551	1.563
	(0.543)	(0.791)	(0.564)	(0.016)	(1.182)	(1.176)	(0.061)	(0.137)
4	1.434	89.871	8.487	0.208	3.262	94.451	0.595	1.692
	(0.542)	(0.795)	(0.568)	(0.016)	(1.183)	(1.175)	(0.065)	(0.143)
5	1.441	89.625	8.721	0.214	3.282	94.365	0.612	1.740
	(0.541)	(0.797)	(0.569)	(0.016)	(1.183)	(1.174)	(0.066)	(0.145)
10	1.442	89.482	8.860	0.216	3.290	94.328	0.623	1.759
	(0.540)	(0.797)	(0.570)	(0.017)	(1.183)	(1.174)	(0.067)	(0.146)
20	1.442	89.481	8.861	0.216	3.290	94.328	0.623	1.759
	(0.540)	(0.797)	(0.570)	(0.017)	(1.183)	(1.174)	(0.067)	(0.146)

Table IA.XXV: Period S_1 11/05/2009 - 02/05/2012, h-trading days ahead Forecast error variance decompositions for financial economy order flows (in %) for state 1 (high) and 2 (low trading intensity state). Columns 2 - 5 represent % variation of financial economy order innovations explained by a unit shock in order innovations from the real economy **Com**, from (own) financial economy **Fin** and intervention innovations **Int** as well as return innovations **FX returns**, respectively. Numbers in brackets represent standard errors from 1000 bootstrap replications.

Table IA.XXVI

Period S_1, h-step ahead Forecast error variance decompositions

for real economy OF (in %) for state 1 (column 2 - 5) and state 2 (column 6 - 9).

	State 1				State 2			
h	**Com**	**Fin**	**Int**	**FX returns**	**Com**	**Fin**	**Int**	**FX returns**
1	95.278	0.005	0.853	3.864	87.315	0.002	0.024	12.659
	(0.618)	(0.212)	(0.221)	(0.580)	(1.733)	(0.089)	(0.007)	(1.731)
2	95.124	0.004	1.106	3.766	87.574	0.002	0.031	12.392
	(0.615)	(0.212)	(0.240)	(0.570)	(1.715)	(0.089)	(0.008)	(1.714)
3	94.661	0.018	1.399	3.922	87.059	0.008	0.040	12.893
	(0.628)	(0.213)	(0.255)	(0.579)	(1.733)	(0.090)	(0.009)	(1.732)
4	94.520	0.020	1.534	3.926	87.026	0.008	0.044	12.922
	(0.630)	(0.213)	(0.260)	(0.579)	(1.734)	(0.090)	(0.009)	(1.733)
5	94.447	0.020	1.603	3.929	87.007	0.009	0.046	12.939
	(0.631)	(0.213)	(0.262)	(0.579)	(1.735)	(0.090)	(0.009)	(1.733)
10	94.398	0.020	1.654	3.928	87.003	0.009	0.047	12.941
	(0.631)	(0.213)	(0.263)	(0.579)	(1.735)	(0.090)	(0.009)	(1.734)
20	94.397	0.020	1.654	3.928	87.003	0.009	0.047	12.941
	(0.631)	(0.213)	(0.263)	(0.579)	(1.735)	(0.090)	(0.009)	(1.734)

Table IA.XXVI: Period S_1 11/05/2009 - 02/05/2012, h-trading days ahead Forecast error variance decompositions for real economy order flows (in %) for state 1 (high) and 2 (low trading intensity state). Columns 2 - 5 represent % variation of real economy order innovations explained by a unit shock in order innovations from (own) real economy **Com**, from the financial economy **Fin** and intervention innovations **Int** as well as return innovations **FX returns**, respectively. Numbers in brackets represent standard errors from 1000 bootstrap replications.

Table IA.XXVII

Period S_1, h-step ahead Forecast error variance decompositions

for BCB interventions (in %) for state 1 (column 2 - 5) and state 2 (column 6 - 9).

	State 1				State 2			
h	**Com**	**Fin**	**Int**	**FX returns**	**Com**	**Fin**	**Int**	**FX returns**
1	0.004	0.058	99.938	0.000	0.114	0.863	99.015	0.009
	(0.004)	(0.033)	(0.033)	(0.000)	(0.135)	(0.511)	(0.531)	(0.063)
2	0.011	0.052	99.930	0.007	0.342	0.765	98.075	0.818
	(0.006)	(0.030)	(0.031)	(0.001)	(0.181)	(0.468)	(0.545)	(0.216)
3	0.011	0.104	99.856	0.028	0.354	1.492	95.102	3.051
	(0.006)	(0.021)	(0.022)	(0.003)	(0.184)	(0.333)	(0.726)	(0.562)
4	0.014	0.117	99.835	0.034	0.429	1.660	94.178	3.733
	(0.006)	(0.019)	(0.020)	(0.003)	(0.196)	(0.305)	(0.820)	(0.666)
5	0.015	0.126	99.821	0.038	0.446	1.774	93.668	4.111
	(0.006)	(0.018)	(0.019)	(0.003)	(0.199)	(0.294)	(0.874)	(0.720)
10	0.015	0.131	99.813	0.040	0.467	1.842	93.336	4.354
	(0.007)	(0.017)	(0.018)	(0.004)	(0.203)	(0.289)	(0.910)	(0.755)
20	0.015	0.131	99.813	0.040	0.468	1.843	93.333	4.356
	(0.007)	(0.017)	(0.018)	(0.004)	(0.203)	(0.289)	(0.910)	(0.755)

Table IA.XXVII: Period S_1 11/05/2009 - 02/05/2012, h-trading days ahead Forecast error variance decompositions for interventions (in %) for state 1 (high) and 2 (low trading intensity state). Columns 2 - 5 represent % variation of real economy order innovations explained by a unit shock in order innovations from the real economy **Com**, from the financial economy **Fin** and (own) intervention innovations **Int** as well as return innovations **FX returns**, respectively. Numbers in brackets represent standard errors from 1000 bootstrap replications.

Table AI.XXVIII

Period S_2, h-step ahead Forecast error variance decompositions for FX returns (in %) for state 1 (column 2 - 4) and state 2 (column 5 - 7).

	State 1			State 2		
h	**Com**	**Fin**	**FX returns**	**Com**	**Fin**	**FX returns**
1	1.449 (1.747)	73.324 (5.643)	25.228 (5.836)	15.327 (0.213)	54.110 (5.562)	30.563 (5.516)
2	1.807 (1.661)	73.086 (5.372)	25.107 (5.639)	18.474 (0.231)	52.128 (5.545)	29.399 (5.491)
3	1.800 (1.652)	72.846 (5.292)	25.354 (5.555)	18.393 (0.229)	51.933 (5.470)	29.674 (5.417)
4	1.814 (1.652)	72.822 (5.281)	25.365 (5.546)	18.512 (0.230)	51.843 (5.469)	29.645 (5.415)
5	1.814 (1.651)	72.821 (5.280)	25.365 (5.545)	18.518 (0.230)	51.839 (5.469)	29.643 (5.415)
10	1.815 (1.651)	72.820 (5.280)	25.365 (5.545)	18.522 (0.230)	51.836 (5.469)	29.642 (5.415)
15	1.815 (1.651)	72.820 (5.280)	25.365 (5.545)	18.522 (0.230)	51.836 (5.469)	29.642 (5.415)
20	1.815 (1.651)	72.820 (5.280)	25.365 (5.545)	18.522 (0.230)	51.836 (5.469)	29.642 (5.415)

Table AI.XXVIII: Period S_2 03/05/2012 - 23/01/2015, h-trading days ahead Forecast error variance decompositions for FX returns (in %) for state 1 (low real economy; high financial economy trade intensity) in column 2 - 4 and state 2 (high real economy; low financial economy trade intensity) in column 5 - 7. Columns 2 and 5 represent % variation of FX return innovations explained by a unit shock in order innovations from the real economy **Com**, columns 3 and 6 from financial economy innovations **Fin**, column 4 and 7 (own) FX return innovations **FX returns** in state 1 and 2, respectively. Numbers in brackets represent standard errors from 1000 bootstrap replications.

Table AI.XXIX

Period S_2, h-step ahead Forecast error variance decompositions

for financial economy OF (in %) for state 1 (column 2 - 4) and state 2 (column 5 - 7).

	State 1			State 2		
h	**Com**	**Fin**	**FX returns**	**Com**	**Fin**	**FX returns**
1	0.116	38.855	61.029	1.181	27.614	71.205
	(0.567)	(5.741)	(5.784)	(0.054)	(6.804)	(6.806)
2	0.114	38.417	61.469	1.158	27.254	71.589
	(0.561)	(5.705)	(5.748)	(0.054)	(6.786)	(6.789)
3	0.114	38.503	61.383	1.156	27.326	71.518
	(0.559)	(5.708)	(5.751)	(0.053)	(6.784)	(6.787)
4	0.114	38.506	61.380	1.160	27.328	71.512
	(0.558)	(5.708)	(5.751)	(0.053)	(6.784)	(6.787)
5	0.114	38.506	61.380	1.160	27.327	71.512
	(0.558)	(5.708)	(5.751)	(0.053)	(6.784)	(6.787)
10	0.114	38.506	61.380	1.161	27.327	71.512
	(0.558)	(5.708)	(5.751)	(0.053)	(6.784)	(6.787)
20	0.114	38.506	61.380	1.161	27.327	71.512
	(0.558)	(5.708)	(5.751)	(0.053)	(6.784)	(6.787)

Table AI.XIX: Period S_2 03/05/2012 - 23/01/2015, h-trading days ahead Forecast error variance decompositions for financial economy order flows (in %) for state 1 (low real economy; high financial economy trade intensity) in column 2 - 4 and state 2 (high real economy; low financial economy trade intensity) in column 5 - 7. Columns 2 and 5 represent % variation in financial economy order flow innovations explained by a unit shock in order innovations from the real economy **Com**, columns 3 and 6 from (own) financial economy innovations **Fin**, column 4 and 7 FX return innovations **FX returns** in state 1 and 2, respectively. Numbers in brackets represent standard errors from 1000 bootstrap replications.

Table AI.XXX

Period S_2, h-step ahead Forecast error variance decompositions for real economy OF (in %) for state 1 (column 2 - 4) and state 2 (column 5 - 7).

	State 1			State 2		
h	**Com**	**Fin**	**FX returns**	**Com**	**Fin**	**FX returns**
1	86.813 (0.242)	10.248 (0.175)	2.939 (0.161)	98.803 (2.588)	0.813 (2.341)	0.383 (1.247)
2	81.806 (0.242)	13.648 (0.145)	4.546 (0.162)	98.232 (2.399)	1.143 (1.910)	0.625 (1.182)
3	81.236 (0.251)	13.262 (0.145)	5.501 (0.175)	98.122 (2.434)	1.117 (1.892)	0.761 (1.264)
4	81.122 (0.252)	13.280 (0.143)	5.598 (0.176)	98.105 (2.428)	1.120 (1.873)	0.775 (1.269)
5	81.087 (0.252)	13.259 (0.143)	5.654 (0.176)	98.098 (2.428)	1.119 (1.869)	0.783 (1.273)
10	81.079 (0.252)	13.256 (0.143)	5.666 (0.176)	98.096 (2.428)	1.119 (1.867)	0.785 (1.274)
20	81.079 (0.252)	13.256 (0.143)	5.666 (0.176)	98.096 (2.428)	1.119 (1.867)	0.785 (1.274)

Table AI.XXX: Period S_2 03/05/2012 - 23/01/2015, h-trading days ahead Forecast error variance decompositions for real economy order flows (in %) for state 1 (low real economy; high financial economy trade intensity) in column 2 - 4 and state 2 (high real economy; low financial economy trade intensity) in column 5 - 7. Columns 2 and 5 represent % variation in real economy order flow innovations explained by a unit shock in order innovations from (own) real economy **Com**, columns 3 and 6 from financial economy innovations **Fin**, column 4 and 7 FX return innovations **FX returns** in state 1 and 2, respectively. Numbers in brackets represent standard errors from 1000 bootstrap replications.

Chapter 4

Evaluation und methodische Weiterentwicklung der Schuldenbremse

Mit finanzieller Unterstützung durch: Fritz Thyssen Stiftung

Abstract

Die Schuldenbremse ist mit dem Inkrafttreten der im Zuge der Föderalismusreform II reformierten Artikel 109 sowie 115 des Grundgesetzes beschlossene Sache. Damit müssen der Bund ab 2016 und die Länder ab 2020 einen im Grundsatz ausgeglichenen Haushalt aufweisen. In diesem Kapitel geht es um die Evaluation der Zuverlässigkeit der bei der Implementierung der Schuldenregel verwendeten ökonometrischen Methodik sowie um die Frage, ob diese Methoden den Kriterien gerecht werden, die an solche Verfahren sowohl aus statistischer als auch aus wirtschafts- und finanzpolitischer Sicht zu stellen sind. Zu diesem Zweck haben wir zunächst anhand von Echtzeitdaten die historische Prognosegüte der Projektionen des Arbeitskreises Steuerschätzungen für das Bruttoinlandsprodukt evaluiert. BIP Prognosen sind zentral für die Ermittlung der Strukturkomponente der Nettokreditaufnahme des Bundes. Zudem stellen sie die maßgebliche Eingangsgröße für die Potentialschätzung im Rahmen der Bestimmung der Konjunkturkomponente der zulässigen Kreditobergrenze des Bundes dar. Die ermittelten Anpassungen der Datengrundlage im Zeitverlauf nutzen wir zur Evaluation des Revisionsbedarfs der Potentialschätzung. Das Kriterium der Planungs- und Budgetsicherheit erlaubt es die Vorteilhaftigkeit verschiedener potentialgebender Verfahren wie sie für die Finanzplanung in Frage kommen gegeneinander zu evaluieren.

Keywords: Fiskal- und Finanzpolitik, quantitative Budgetsicherheit, Produktionspotentialschätzung der EU Kommission, Schuldenbremse, Prognoseevaluation Arbeitskreis Steuerschätzungen.

JEL classification: C22, C52, C53, H11, H68, H87

4.1 Einleitung

Die Schuldenbremse ist mit dem Inkrafttreten der im Zuge der Föderalismusreform II reformierten Artikel 109 sowie 115 des Grundgesetzes beschlossene Sache. Durch die Aufnahme in das Grundgesetz der Bundesrepublik Deutschland wurde zum ersten Mal eine verbindliche Regel etabliert, die einer seit über 40 Jahren wachsenden Staatsverschuldung sowohl in absoluten Zahlen als auch in Relation zur Wirtschaftsleistung begegnen soll. Damit müssen der Bund ab 2016 und die Länder ab 2020 einen im Grundsatz ausgeglichenen Haushalt aufweisen. Von den Befürwortern der Schuldenbremse wurde argumentiert, dass diese zu einer nachhaltigen Finanzpolitik beitrage sowie der intergenerationalen Gerechtigkeit Genüge tue (vgl. z.B. Schäuble, 2013; Burret, 2013). Demgegenüber gab es auch Kritik, die vor allem darauf abzielte, dass durch die Schuldenbremse eine eindimensionale Zielsetzung der Finanzpolitik verfolgt und u.a. notwendige vorsorgende Investitionen in Bildung, Infrastruktur und Umwelt vernachlässigt würden (vgl. u.a. Bofinger und Horn, 2009).
Aus finanzpolitischer Sicht hat die Schuldenbremse zudem den Vorteil, dass sie bei einer verlässlichen methodischen Umsetzung dabei hilft unerwünschte Finanzierungslücken in der Haushalts- und Finanzplanung durch eine Glättung der Einnahmeseite um konjunkturbedingte Schwankungen zu vermeiden. Dies ist insbesondere dann der Fall wenn Bund, Länder und Kommunen dann auch ihre langfristigen Ausgaben an den konjunkturbereinigten, langfristigen Einnahmen orientieren (vgl. auch Haas und Müller, 2012).
Aus fiskal- und wirtschaftspolitischer Sicht sind Abweichungen vom Produktionspotential, d.h. große Schwankungen der gesamtwirtschaftlichen Aktivität ebenfalls nicht wünschenswert. Zum einen kommt es aus gesamtwirtschaftlicher Sicht zu steigendem Inflationsdruck in Aufschwungphasen und zum anderen zu steigender Arbeitslosigkeit in Abschwungphasen, die insbesondere in Deutschland seit den 1970ger Jahren immer wieder auch in einer steigenden konjunkturunabhängigen Sockelarbeitslosigkeit mündeten. Neben weiteren fiskalischen Maßnahmen wie den automatischen Stabilisatoren[1] sieht das Grundgesetz daher die Möglichkeit vor über eine antizyklische Ausgabenpolitik der öffentlichen Hand zu einer nachfrageseitigen Dämpfung der konjunkturellen Schwankungen des Bruttoinlandsproduktes beizutragen.[2]
Zur Erreichung dieser Ziele wird im Rahmen der mittelfristigen Finanzplanung eine Obergrenze für die Nettokreditaufnahme bestimmt, die im Wesentlichen aus zwei Komponenten besteht. Das geltende Finanzverfassungsrecht verlangt dabei, das "Einnahmen und Ausgaben (...) grundsätzlich ohne Einnahmen aus Krediten auszugleichen (sind). Diesem Grundsatz ist entsprochen, wenn die Einnahmen aus Krediten 0,35 vom Hundert im Verhältnis zum nominalen Bruttoinlandsprodukt nicht überschreiten. (...)".[3] Die letzte Forderung mündet dabei in der sogenannten Strukturkomponente der Obergrenze für die Nettokreditaufnahme.
Darüber hinaus dürfen der Bund und die Länder ihre Ausgaben kurzfristig, d.h. in konjunkturell schlechten Zeiten um eine sogenannte Konjunkturkomponente kreditfinanziert erhöhen

[1] Unter automatischen Stabilisatoren versteht man stützende fiskalpolitische Maßnahmen, die nahezu ohne Vorlaufzeit stabilisierende Wirkung auf die gesamtwirtschaftliche Entwicklung entfalten. Hierzu zählt beispielsweise die Arbeitslosenversicherung.

[2] vgl. Grundgesetz für die Bundesrepublik Deutschland (GG) Artikel 109 (2) sowie Gesetz zur Förderung der Stabilität und des Wachstums der Wirtschaft (StabG), 1967.

[3] vgl. GG, Artikel 109 (3) sowie 115 Abs. (2).

um im Gegenzug diese Kredite in guten Phasen in voller Höhe und damit *symmetrisch* wieder zurückzuführen (vgl. auch Kastrop und Snelting, 2008; GG Artikel 109 und 115).
Der zentrale Aspekt dieser Schuldenregel ist dabei die Bestimmung der im Grundgesetz verankerten "Normallage" der gesamtwirtschaftlichen Entwicklung, d.h. die Schätzung des nicht beobachtbaren Produktionspotentials sowie die sich aus dieser Schätzung ergebenden Produktionslücken.
Die Haushaltsbudgets des Bundes und der Länder sind darüber hinaus in einer Finanzplanung vorausschauend darzustellen.[4] Dies hat für die Umsetzung der Schuldenbremse zwei Konsequenzen. Zum einen muss das Bruttoinlandsprodukt (BIP) unter Unsicherheit prognostiziert werden um die Strukturkomponente zu bestimmen. Zum anderen muss aber auch die Schätzung des nicht beobachtbaren Produktionspotentials auf Basis dieser BIP-Projektionen erstellt werden, da die hieraus abgeleitete Konjunkturkomponente ebenfalls für zukünftige Haushaltsjahre darzustellen ist.
In diesem Kapitel soll es nicht um das Für und Wider der Schuldenbremse gehen, denn diese ist zum gegenwärtigen Zeitpunkt beschlossene Sache. Uns geht es vielmehr um die Evaluation der Zuverlässigkeit der bei der Implementierung der Schuldenregel verwendeten ökonometrischen Methodik sowie um die Frage, ob diese Methoden den Kriterien gerecht werden, die an solche Verfahren sowohl aus statistischer als auch aus wirtschafts- und finanzpolitischer Sicht zu stellen sind.
Zu diesem Zweck evaluieren wir die historischen BIP Prognosen der Bundesregierung wie sie zur Bestimmung der Strukturkomponente notwendig sind. Zur Schätzung des Produktionspotentials für die Bundesrepublik Deutschland verwendet die Bundesregierung unter Federführung des Bundesministerium für Wirtschaft und Energie (BMWi) im Kern ein Konjunkturbereinigungsverfahren der EU Kommission. Daher zeigen wir die Auswirkungen historischer Prognosefehler und statistischer Revisionen des BIP auf die Stabilität der Schätzung und Prognose des Produktionspotentials sowie der Produktionslücken anhand verschiedener potentialgebender Verfahren auf.
Zur Evaluation der Schuldenbremse nutzen wir die öffentlich verfügbaren Methoden der EU Kommission sowie zeitgleich veröffentlichte, historische Echtzeitdatenstände des deutschen BIP. Zudem verwenden wir zur Berechnung historischer Prognosefehler Wachstumsprognosen des BIP wie sie im Rahmen der Sitzungsergebnisse des Arbeitskreises Steuerschätzungen publiziert und für die Steuerschätzungen des Bundes und der Länder im Untersuchungszeitraum zur Anwendung gekommen sind. Im Zuge der Finanzplanung des Bundes und der Länder findet dabei eine halbjährliche Aktualisierung der verwendeten Datenbasis statt.[5] Zudem unterliegt das BIP im Zeitverlauf weiteren statistischen Revisionen.
Durch die Verwendung historischer Echtzeitdaten sind wir in der Lage, die Auswirkungen von Datenrevisionen auf die Punktschätzung von Produktionspotential und -lücke abzubilden sowie die Berichterstattung im Rahmen der Finanzplanung um verfahrensspezifische Unsicherheitsbereiche in Form von Fancharts zu erweitern. Diese Unsicherheitsmaße können dann als Kriterium für die Planungssicherheit zukünftiger Budgets der öffentlichen Hand sowie zu einer

[4]vgl. Gesetz zur Förderung der Stabilität und des Wachstums der Wirtschaft (StabG) von 1967.
[5]vgl. auch Gesetz zur Förderung der Stabilität und des Wachstums der Wirtschaft (StabG) von 1967.

ersten Einschätzung der Einhaltung der Schuldenbremse dienen. Auf dieser Basis lassen sich dann auch konkurrierende Verfahren bezüglich ihres individuellen Revisionsbedarfs vergleichen.
Ein immer wieder geäußerter Kritikpunkt an der Methode der EU Kommission ist die Komplexität des Verfahrens an sich. So argumentieren neben anderen Holtemöller et al. (2013), dass Komplexität und Manipulationsanfälligkeit eines Konjunkturbereinigungsverfahrens korreliert sind. Aus diesem Grund lässt sich fragen in wie weit weniger komplexe Verfahren eine vergleichbare oder sogar geringere Anfälligkeit für BIP-Revisionen aufweisen und somit letztlich die Planungssicherheit der öffentlichen Haushalte erhöhen würden.
Unsere Ergebnisse für die Bundesrepublik Deutschland legen nahe, dass der zu einem früheren Zeitpunkt durch die EU Kommission verwendete Hodrick-Prescott Filter für zukünftige Haushaltsjahre weniger revisionsanfällig ist als das aktuelle Verfahren der EU Kommission zur Bestimmung des deutschen Produktionspotentials. Gleichzeitig erweist sich der HP Filter dabei als methodisch relativ simpel und daher auch als transparenter, unanfälliger gegen Manipulationen und letztlich auch als kostengünstiger in der administrativen Anwendung.
Der Rest dieser Arbeit gliedert sich wie folgt. Kapitel 4.2 gibt einen Überblick über die Methodik der deutschen Schuldenbremse sowie alternativer Verfahren zur Bestimmung des Produktionspotentials. Kapitel 4.3 beschreibt die verfügbare Datenbasis und Evaluation anhand des Kriteriums der verfahrensspezifischen Planungs- und Budgetsicherheit. Kapitel 4.4 stellt die empirischen Ergebnisse vor und vergleicht die Verfahren anhand der Kriterien Revisionsanfälligkeit, Höhe des ausgewiesenen Produktionspotentials sowie der resultierenden verfahrensspezifischen Produktionslücken. Kapitel 4.5 fasst abschließend zusammen.

4.2 Methodik der Schuldenbremse

Im Gegensatz zum direkt mess- und beobachtbaren BIP handelt es sich beim Produktionspotential um eine nicht beobachtbare und daher zu schätzende Größe. Im Rahmen der Schuldenbremse wird das Produktionspotential dabei in der der Regel als inflationsneutrale Kapazitätsauslastung der Produktion definiert. In konjunkturell guten Zeiten liegt die aktuelle Produktion in Form des BIP dann über dem Potential was zu Inflationsdruck führt, während das BIP in schlechten Zeiten entsprechend unterhalb des Potentials verläuft. Diese sich so ergebenden positiven und negativen Abweichungen zwischen BIP- und Potentialpfad werden dementsprechend als Produktionslücken bezeichnet.
Eine ausführliche Beschreibung der Bundesmethode findet sich beispielsweise in Kastrop und Snelting (2008), wobei die wesentlichen Aspekte hier im Folgenden wiedergegeben werden. Im Kern geht es bei der Schuldenbremse um die Bestimmung der zulässigen Obergrenze für die Nettokreditaufnahme des Bundes. Diese berechnet sich dabei wie folgt:
Wie aus Abbildung 1 ersichtlich setzt sich die zulässige Nettokreditaufnahme dabei aus 4 Komponenten zusammen, wobei lediglich die Struktur- sowie die Konjunkturkomponente in der empirischen Anwendung Spielraum für diskretionäre Entscheidungen lassen.
Für die Strukturkomponente (SK) gilt dies, da sie sich anteilig an den geschätzten BIP Prog-

Obergrenze für die Nettokreditaufnahme =	
	Strukturkomponente (0,35 % des BIP)
+/-	Konjunkturkomponente
+/-	Saldo der finanziellen Transaktionen gemäß § 2 Abs. (2) Sanktionsaufteilungsgesetz
-	Gegebenenfalls abzubauende Überschreitung des Kontrollkontos

Abbildung 1: Schema zur Berechnung der Kreditobergrenze nach der Bundesmethode; der Methode des BMF (Quelle: Kastrop und Snelting 2008, Tabelle 1, Seite 376)

nosen ($\hat{Y}_h$) der kommenden Haushaltsjahre $h = 1, ..., H$ wie folgt berechnet

$$SK_h = \hat{Y}_h \times 0,035 \tag{4.1}$$

Diese BIP Prognosen werden dabei durch die Bundesregierung erstellt. Die Berechnung der Konjunkturkomponente wird laut Kastrop und Snelting (2008) in mehreren Schritten vorgenommen.[6] Die zentrale Bestimmungsgröße ist hier das geschätzte Produktionspotential ($\hat{Y}^P$) bzw. die sich aus diesem ergebenden Produktionslücken (OG_h) der kommenden Haushaltsjahre,

$$OG_h = \hat{Y}_h - \hat{Y}_h^P, \quad h = 1, ..., H \tag{4.2}$$

In einem zweiten Schritt berechnet sich die Konjunkturkomponente (CC_h) für die Finanzplanung der kommenden Haushaltsjahre dann als

$$CC_h = \hat{\epsilon} \times OG_h, \quad h = 1, ..., H \tag{4.3}$$

wobei $\hat{\epsilon}$ die geschätzte Budgetsensitivität bzw. Budgetsemielastizität beschreibt. Hier wird auf Vorarbeiten der OECD zurückgegriffen, die die Budgetsensitivität für Deutschland und weitere OECD Mitglieder geschätzt hat.[7] Dementsprechend fußt auch die Konjunkturkomponente auf den BIP Prognosen der Bundesregierung sowie auf der aktuellen Methodik zur Bestimmung des Produktionspotentials und der Produktionslücke der EU Kommission.[8]
Zur Schätzung des Produktionspotentials kommen in der Regel zwei Klassen von Verfahren in Frage, die jeweils ihre spezifischen Vor- und Nachteile haben (vgl. z.B. Haas und Müller, 2012; Sachverständigenrat zur Begutachtung der gesamtwirtschaftlichen Entwicklung (SVR), 2003, S.412ff).
Zum einen kann hier die Klasse der statistischen Filterverfahren zur Anwendung kommen.

[6]Vgl. auch die Erläuterungen in "Gesamtwirtschaftliches Produktionspotential und Konjunkturkomponenten" Datengrundlagen und Ergebnisse der Schätzungen der Bundesregierung. Stand: Frühjahrsprojektion 22.04.2015.

[7]vgl. Girouard und Andre (2005) und Mourre et al. (2013) sowie Mourre et al. (2014). Die Bundesregierung rechnet dabei zurzeit mit einer Budgetsemielastizität von 0,205.

[8]vgl. die Erläuterungen in "Gesamtwirtschaftliches Produktionspotential und Konjunkturkomponenten" Datengrundlagen und Ergebnisse der Schätzungen der Bundesregierung. Stand: Frühjahrsprojektion 22.04.2015.

Diese Verfahren haben den Vorteil, dass sie in der Regel relativ simpel und daher eher transparent, nachvollziehbar und letztlich auch manipulationsunanfälliger sind (vgl. SVR, 2007). Ein je nach Sichtweise weiterer Vor- bzw. Nachteil ist, dass diese Verfahren in der Regel nur die Information der BIP Zeitreihe selbst verwenden. Ein prominenter Vertreter ist hier der Hodrick Prescott (HP) Filter,[9] der im Rahmen der Schweizer Schuldenbremse (vgl. auch Bruchez, 2003; Columbier et al., 2004) sowie als Parallelverfahren durch die EU Kommission zur Anwendung kommt (vgl. Havik et al., 2014). Diese Filterverfahren sind in der Regel einfacher zu durchschauen und hängen von wenigen Parametern ab, wodurch eine strikt regelgebundene Politik unter Umständen einfacher gewährleistet werden kann. Einfache Modelle, die aber die wesentlichen Charakteristika der Daten widerspiegeln, erweisen sich in der Ökonometrie oft auch als besser geeignet, wenn es um die Erstellung von echten out-of-sample Prognosen geht, auf deren Zurückgreifen im Rahmen der Haushaltsplanung ja nicht verzichtet werden kann.[10] Im Gegensatz hierzu verwenden theoriefundierte Verfahren wie der Produktionsfunktionsansatz der EU Kommission die Information mehrerer Zeitreihen zur Bestimmung des Potentials (vgl. Havik et al., 2014). Diese greifen dabei aber ebenfalls auf statistische Filterverfahren zurück um die Trends der Unteraggregate des Potentials zu bestimmen. Diese strukturellen Modelle können dann auch für Szenarioanalysen Verwendung finden, die über alternative Verläufe des BIP hinausgehen. Ein Nachteil, der sich zwangsläufig hieraus ergibt ist, dass diese Verfahren schnell an Komplexität gewinnen. Zudem werden für theoriefundierte Modelle neben den Projektionen des BIP zusätzliche Prognosen aller weiteren verwendeten Inputgrößen benötigt.

4.2.1 Verfahren der EU Kommission

Das Verfahren der EU Kommission verwendet zur Bestimmung des Produktionspotentials einen theorie-fundierten Ansatz (vgl. Havik et al., 2014). Dabei wird zunächst folgende Cobb-Douglas Produktionsfunktion für das BIP (Y) zugrunde gelegt,

$$Y = (U_L L E_L)^{\alpha} (U_K K E_K)^{1-\alpha} \tag{4.4}$$

wobei als Produktionsfaktoren hier Arbeit (L) und Kapital (K) unterstellt werden. Zudem wird die Kapazitätsauslastung (U) der Faktoren sowie die Effizienz (E) berücksichtigt. Diesem Ansatz liegen bereits zwei implizite Annahmen zu Grunde. Zum einen wird davon ausgegangen das die Ökonomie unter konstanten Skalenerträgen wächst, d.h. dass sich die Produktionselastizitäten α, $\beta = 1 - \alpha$ zu eins addieren. Zum anderen wird unterstellt, dass die Preiselastizitäten der Faktoren gleich eins sind. Gleichung (4.4) lässt sich dann auch wie folgt formulieren,

$$Y = L^{\alpha} K^{1-\alpha} A \tag{4.5}$$

wobei hier (A) die totale Faktorproduktivität bzw. definitionsgemäß den technischen Fortschritt beschreibt. Für das langfristige Produktionspotential der Ökonomie lässt sich an-

[9] vgl. Hodrick und Prescott, 1997.

[10] vgl. auch Haas und Müller 2012 sowie für eine allgemeine Diskussion z.B. Box et al., 2008.

nehmen

$$U_L = U_K = 1, \tag{4.6}$$

sodass von einer Normalauslastung der Produktionsfaktoren entlang des Potentialpfades ausgegangen wird. Die langfristige Entwicklung des BIP bzw. des Produktionspotentials (Y^P) ergibt sich dann als

$$Y^P = (L^P E_L^P)^\alpha (K E_K^P)^{1-\alpha} \tag{4.7}$$

mit dem potentiellen Arbeitsangebot (L^P) und der potentiellen Effizienz der jeweiligen Produktionsfaktoren (E^P). Analog zum kurzfristigen Konzept für das BIP in Gleichung (4.4) und (4.5) lässt sich der Trend der totalen Faktorproduktivität (TA) dann als

$$TA = (E_L^P)^\alpha (E_K^P)^{1-\alpha} \tag{4.8}$$

darstellen. In Gleichung (4.7) fällt auf, dass der Faktor Kapital (K) bereits als langfristige Größe betrachtet wird. Die EU Kommission stellt fest, dass der Kapitalstock einer Ökonomie nur geringer Volatilität unterliegt, insbesondere da Nettoinvestitionen nur einen geringen Anteil am bestehenden Kapitalstock darstellen (vgl. Havik et al., 2014). Darüber hinaus wird angenommen, dass die Produktionselastizitäten des Faktors Arbeit α mit 0,63 und die Elastizität des Kapitals $\beta = 1 - \alpha$ entsprechend mit 0,37 gegeben sind. Diese Größen orientieren sich laut Kommission dabei an einer Schätzung der Lohnquote für die EU15 Staaten über den Zeitraum von 1960 bis 2003. Dementsprechend verbleiben nach der Methode der EU Kommission zur Ermittlung des Produktionspotentials nach Gleichung (4.7) noch die Bestimmung des Trends der totalen Faktorproduktivität (TA) sowie des potentiellen Arbeitsangebots (L^P).

Das nicht beobachtbare potentielle Arbeitsangebot (L^P) wird nach einem Arbeitsstundenkonzept in einem mehrstufigen Verfahren bestimmt. Zu diesem Zweck wird zunächst der Trend der Partizipationsrate mit Hilfe des HP Filters ermittelt.[11] In einem nächsten Schritt wird unter Zuhilfenahme des Konzeptes der "non-accelerating wage rate of unemployment" (NAWRU) die Trendarbeitslosigkeit sowie der Beschäftigungstrend bestimmt (vgl. für die Ausgestaltung der NAWRU der EU Kommission Orlandi, 2012). Zudem wird der Trend der durchschnittlichen Arbeitsstunden mit dem HP Filter ermittelt. Abschließend erhält man das nicht beobachtbare potentielle Arbeitsangebot (L^P) als Produkt des Beschäftigungstrends und des Trends der durchschnittlichen Arbeitsstunden.

Bei der totalen Faktorproduktivität (A) handelt es sich wie beim Produktionspotential selbst um eine nicht beobachtbare und daher zu schätzende Größe. In der Regel werden daher die geschätzten Solow Residuen eines log-linearisierten und differenzierten Modells nach Gleichung (4.4) bzw. (4.5) als totale Faktorproduktivität interpretiert (vgl. z.B. SVR, 2003). Im Sinne von Gleichung (4.7) bzw. (4.8) gilt es dann im Anschluss den Trend der Faktorproduktivität zu bestimmen. Unter einer Reihe von möglichen trendextrahierenden Verfahren, wie dem in Kapitel 4.2.2 beschriebenen HP Filter, wählt die EU Kommission hier einen bivariaten Kalman Filter (vgl. z.B. Hamilton, 1994). Dieser arbeitet unter der Annahme, dass die zyklis-

[11] Die Partizipationsrate ist dabei definiert als der Quotient aus der Summe aller Arbeitsnehmer und Erwerbslosen anteilig an der Gesamtpopulation im erwerbsfähigen Alter zwischen 15 und 64 Jahren.

che Komponente der totalen Faktorproduktivität (A) über den Konjunkturzyklus hinweg dem Grad der Kapazitätsauslastung (U) der Ökonomie folgt. Bei dieser Vorgehensweise zur Bestimmung des Trends der totalen Faktorproduktivität (TA) handelt es sich dementsprechend um ein zweistufiges Schätzverfahren, wobei jede Stufe für sich unter Unsicherheit erfolgen muss.

4.2.2 Der HP Filter

Statistischen Filterverfahren,[12] insbesondere auch der Hodrick Prescott (HP) Filter, zerlegen die Beobachtungen $t = 1, ..., T$ des BIP (Y_t) in eine zyklische Komponente (Z_t) und eine entsprechend glatte Trendkomponente (Y_t^*), sodass

$$Y_t = Y_t^* + Z_t. \tag{4.9}$$

Im Falle der Zerlegung des BIP lässt sich die Trendkomponente (Y_t^*) dann analog zur Methode der EU Kommission als Schätzung des inflationsneutralen Produktionspotentials (Y^P) interpretieren. An die Zerlegung mit Hilfe des HP Filters werden dabei zwei Forderungen gestellt (vgl. auch Leser, 1961; Hodrick und Prescott, 1997 oder Haas und Müller, 2012). Zum einen soll sich die Potentialschätzung über den Beobachtungszeitraum insgesamt gut an die Datenpunkte der BIP Zeitreihe anpassen um somit die Entwicklung der Produktion adäquat nachzuzeichnen. Zum anderen soll das geschätzte Potential aber auch möglichst geringen Schwankungen unterliegen, da starke Schwankungen einer langfristigen Größe wie dem Produktionspotential einer Volkswirtschaft ökonomisch kontraintuitiv wären. Die zweite Forderung wird beim HP Filter durch die Veränderung der Wachstumsraten der Trendfunktion (Y_t^*) formalisiert[13]

$$\Delta^2 Y_{t+1}^* = \Delta Y_{t+1}^* - \Delta Y_t^* = (Y_{t+1}^* - Y_t^*) - (Y_t^* - Y_{t-1}^*). \tag{4.10}$$

Misst man zudem die Anpassung der Trendfunktion an die Zeitreihe des BIP über die Summe der quadratischen Abweichungen zwischen BIP (Y_t) und dessen langfristigem Trend (Y_t^*) führt dies auf das Minimierungsproblem des HP Filters

$$\min_{Y_1^*, ..., Y_T^*} \sum_{t=1}^{T} (Y_t - Y_t^*)^2 + \lambda \sum_{t=2}^{T-1} [(Y_{t+1}^* - Y_t^*) - (Y_t^* - Y_{t-1}^*)]^2, \tag{4.11}$$

wobei der einzig festzulegende Parameter (λ) als Maß für die Länge des Konjunkturzyklus interpretiert werden kann. In der Literatur herrscht weitestgehend Konsens darüber, dass für die Zerlegung von jährlichen BIP Daten ein $\lambda = 100$ gewählt werden sollte (vgl. SVR,

[12] vgl. Hodrick und Prescott, 1997; Kydland und Prescott, 1990 sowie Mills, 2003 für einen Überblick über grundliegende Konzepte und Lösungsansätze.

[13] D.h. im vorliegenden Fall durch die zweiten Differenzen des logarithmierten BIP.

2007).[14] Da dies zudem die einzige Annahme dieses Ansatzes ist, schlussfolgert der Sachverständigenrat zur Begutachtung der gesamtwirtschaftlichen Entwicklung,

"Der Sachverständigenrat verwendet den HP Filter zur Potentialschätzung und zusätzlich in anderen Bereichen, wie beispielsweise bei der Ermittlung des konjunkturbereinigten staatlichen Defizits. Für den HP Filter sprechen in diesem Zusammenhang vor allem dessen Einfachheit und das Kriterium der Transparenz, da der HP Filter in der empirischen Anwendung vergleichsweise wenig Spielraum für Willkür lässt." (SVR, 2007, "Staatsverschuldung wirksam begrenzen", S.136)

Die Verwendung des HP Filters im Zuge der Schuldenbremse hat dabei weitere Vorteile. Zunächst ist der HP Filter im Einklang mit dem geltenden Finanzverfassungsrecht zu sehen. So fordert das GG in Artikel 109 (3) sowie 115 (2), dass die Summe der Konjunkturkomponenten über den Konjunkturzyklus hinweg gleich Null sein soll. Diese auch als Symmetriekriterium bekannte Forderung wird vom HP Filter ex ante nahezu perfekt erfüllt,[15] sodass bei Zugrundelegung eines hinreichend langen Beobachtungszeitraums auch unter diesem Aspekt die gesetzlichen Anforderungen erfüllt sind und ein Symmetriekonto über den Konjunkturzyklus hinweg stets nahezu ausgeglichen ist.
Ein bekannter Nachteil ist jedoch das sogenannte Randwertproblem des HP Filters. So reagieren die Trendschätzungen an den Beobachtungsrändern tendenziell stärker auf BIP Revisionen.[16] Dies kann insbesondere am aktuellen Datenrand problematisch sein, da hier im Zuge der Haushaltsplanung fortlaufend Soll- durch Ist-Größen ersetzt sowie statistische Revisionen der Ist-Größen durch das Statistische Bundesamt vorgenommen werden. Zur Lösung des Randwertproblems haben sich dabei zwei Ansätze etabliert. Zum einen kann diesem Problem durch eine Modifikation des Gewichtungsschemas der Randbeobachtungen entgegengewirkt werden.[17] Zum anderen kann die zu filternde Zeitreihe auch durch Projektionen verlängert werden, um das Randwertproblem über die planungsrelevanten Perioden hinaus in die Zukunft zu verschieben. Letztere Vorgehensweise wurde dabei von der EU Kommission gewählt, die die BIP Grundlage entsprechend zeitreihenökonometrischer Standardmodelle in die Zukunft projiziert.[18] Da diese Arbeit aber gerade das Ziel der quantitativen Evaluation

[14] Im Gegensatz hierzu zeigen Ravn und Uhlig, 2002 in einer analytischen Analyse, dass für jährliche Daten ein $\lambda = 6,25$ gewählt werden sollte. Wir wählen in unserer Analyse dennoch ein $\lambda = 100$ analog zur Vorgehensweise der EU Kommission in Havik et al., 2014.

[15] In der Regel wird der HP Filter auf das logarithmierte BIP angewendet. Dann ist die Summe der zyklischen Komponenten (Z_t) nahe Null. Verwendet man das BIP selbst ist ($\sum_{t=1}^{T} Z_t = 0$). Gleiches gilt dann für die Konjunkturkomponente nach der Bundesmethode (vgl. Kapitel 4.2).

[16] Dies wird offenbar aus Gleichung (4.11). Hier werden die ersten beiden und letzten beiden Beobachtungen seltener im Strafterm berücksichtigt als die restliche Datenbasis.

[17] Diese Vorgehensweise wurde beispielsweise im Rahmen der Schweizer Schuldenbremse gewählt (vgl. Bruchez, 2003) und wurde dagegen aber im Falle der Schuldenbremse für Schleswig-Holstein quantitativ evaluiert und keine Vorteilhaftigkeit festgestellt (vgl. Haas und Müller, 2012).

[18] Sofern nicht anders beschrieben, verwendet die EU Kommission zur Projektion der relevanten Größen im Rahmen der Schuldenbremse univariate ARIMA Modelle (vgl. Havik et al., 2014). Bei Verwendung des HP Filters werden darüber hinaus 3 zusätzliche Perioden in die Zukunft projiziert um dem Randwertproblem zu begegnen.

der Revisionsanfälligkeit der Potentialschätzung durch eine veränderte BIP Datenbasis hat wird dieser Aspekt in Kapitel 4.3 und 4.4 noch näher beleuchtet.

4.3 Verwendete Datenbasis und Evaluation

Wie vom Sachverständigenrat zur Begutachtung der gesamtwirtschaftlichen Entwicklung festgestellt, kann die Güte konkurrierender Verfahren zur Schätzung des nicht beobachtbaren Produktionspotentials nicht ohne weiteres quantitativ evaluiert werden (vgl. SVR, 2003, S.412, Ziffer 737). Wir nutzen zu diesem Zweck eine Echtzeitdatenbank des BIP und stellen die Frage, welche Auswirkungen historische Revisionen und Prognosefehler des BIP auf die Schätzung von Potential und Produktionslücke und damit letztlich auf die Planungssicherheit zukünftiger, öffentlicher Budgets haben.
Für das reale Bruttoinlandsprodukt stehen uns biannuale historische Echtzeitdatenstände über den Zeitraum Herbst 2004 bis Frühjahr 2015 zur Verfügung. Diese Daten wurden jeweils zusammen mit der aktuellen Programmversion durch die EU Kommission zur Verfügung gestellt und entsprechen den historischen AMECO[19] Datenständen. Zudem verwenden wir Mittelfristprojektionen des realen BIP für einen Prognosehorizont von $h = 1, ..., 5$ Jahren. Wie in der mittelfristigen Finanzplanung der öffentlichen Hand üblich, entspricht $h = 1$ dabei dem laufenden Haushaltsjahr, $h = 2$ dem kommenden Jahr und so weiter. Für diese Projektionen haben wir aus den Echtzeitprognosen der nominalen Wachstumsraten des BIP, wie sie in den Sitzungsergebnissen des "Arbeitskreises Steuerschätzungen" (AKS) protokolliert sind, reale Wachstumsraten errechnet und den zugehörigen Echtzeitdatenstand vom damaligen aktuellen Rand aus fortgeschrieben. Aus diesen so projizierten Reihen haben wir im Anschluss die Jahr-zu-Jahr Differenz der Echtzeitdatenstände des realen BIP berechnet.[20]
Unter Revisionen subsummieren wir daher sowohl statistische Revisionen der Datenbasis als auch Prognoserevisionen der Bundesregierung, die sich in einem horizontgerechten Prognosefehler zukünftiger Haushaltsjahre $h = 1, ..., 5$ des realen BIP niederschlagen.
Um die konkurrierenden potentialgebenden Verfahren aus Kapitel 4.2 quantitativ zu evaluieren, stellen wir die Frage, welche Auswirkungen die historischen Prognosefehler des realen BIP am aktuellen Datenrand auf die Schätzung des Potentials unter Verwendung des aktuellen Produktionsfunktionsansatzes der EU Kommission sowie des HP Filters gehabt hätten. Hierzu werden zunächst die historischen Prognosefehler $e_{t+h|I_t}$ des realen BIP $\hat{Y}_t^r$ zum Informationsstand I wie er zum Zeitpunkt t gegeben ist aus den Jahr zu Jahr Revisionen der Mittelfristprojektionen der Haushaltsjahre h als,

$$\hat{e}_{t+h|I_t} = \hat{Y}^r_{t+h|I_{t+1}} - \hat{Y}^r_{t+h|I_t}, \quad h = 1, ..., 5 \tag{4.12}$$

[19] Annual Macro Economic database of the European Commission (AMECO)
[20] Da der Arbeitskreis "Steuerschätzungen" erst seit der Herbstschätzung 2011 den gesamten Mittelfristzeitraum abdeckt, d.h. auch im Herbst das BIP volle 5 Jahre in die Zukunft fortschreibt haben wir mit den Datenständen der Frühjahrsprojektionen für den Zeitraum 2005 bis 2015 gearbeitet (vgl. BMF, 2015).

berechnet. Anschließend werden die historischen Revisionen horizontgerecht zu dem aktuellen BIP Datenstand $\hat{Y}^r_{t|I_{2015}}$ der Bundesregierung aus dem Frühjahr 2015 addiert,

$$\hat{Y}_i^{EA} = \begin{cases} \hat{Y}^r_{t|I_{2015}} & \text{für} \quad t = 1980, ..., 2014 \\ \hat{Y}^r_{t+h|I_{2015}} + \hat{e}_{t+h|I_t} & \text{für} \quad t+h = 2015, ..., 2019 \end{cases} \tag{4.13}$$

um so eine Anzahl $i = 1, ..., N$ ex ante BIP-Szenarien $\hat{Y}_i^{EA}$ zu erhalten.[21] Diese BIP-Szenarien dienen dann als Input für die jeweiligen potentialgebenden Verfahren, sodass wir als Resultat entsprechende Szenarien für die zukünftige Entwicklung des Produktionspotentials erhalten. Die Potentialschätzung auf aktueller Datenbasis $\{\hat{Y}^P_{t|I_{2015}}\}_{t=1980}^{2019}$, die auf der größten verfügbaren Informationsmenge I_{2015} beruht, sehen wir als ex post Stand des Potentials an. Die Abweichungen zwischen dem geschätzten ex post Potential $\{\hat{Y}^P_{h|I_{2015}}\}_{h=1}^{5}$ sowie den ex ante Potentialszenarien $\{\hat{Y}^{P,SZ}_{h|I_t}\}_{h=1}^{5}$ unter Berücksichtigung historischer Prognosefehler des BIP interpretieren wir dann analog zu beobachtbaren Größen als verfahrensspezifische Prognosefehler des Produktionspotentials. Aus diesem Prognosefehler leiten wir wiederrum klassische (frequentistische) horizontgerechte Standardfehler der Potentialprognose in der aktuellen Mittelfrist als,

$$\sigma_h = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{Y}^P_{h|I_{2015}} - \hat{Y}^{P,EA}_{h|I_t})^2}, \quad h = 1, ..., 5 \tag{4.14}$$

ab (vgl. auch Haas und Müller 2012 und Boysen-Hogrefe et al. 2014). Eine geringere verfahrensspezifische Prognoseunsicherheit σ_h in den relevanten Haushaltsjahren h geht dann mit einer höheren Planungssicherheit für die Budgets der öffentlichen Hand einher.[22]

Wie im vorangegangenen Kapitel beschrieben unterscheiden sich die beiden Verfahren zur Bestimmung des Potentials auch maßgeblich in Hinsicht auf die verwendeten Inputdaten. Während für den HP Filter nur die extrapolierte Zeitreihe des BIP verwendet wird müssen zur Anwendung der EU Methode zudem weitere Inputdaten zur Verfügung gestellt werden. Alle notwendigen Inputs in unserer Analyse entsprechen dabei den Datenständen wie sie gemeinsam mit der hier evaluierten Programmversion des Frühjahres 2015 von der EU Kommission veröffentlicht wurden. Eventuell zusätzlich notwendige Projektionen werden zudem von diesem Programm selbstständig unter Verwendung ökonometrischer Standardmodelle erstellt (vgl. Havik et al., 2014).[23]

Neben der Möglichkeit Szenario Rechnungen des BIP zu erstellen erlaubt das Programm der Kommission darüber hinaus auch explizit die Berücksichtigung abweichender Prognosen der Wachstumsraten der Erwerbstätigen, der Bruttoanlageinvestitionen, der harmonisierten Ar-

[21] Am aktuellen Rand der Echtzeitdaten konnten die historischen Prognosefehler $e_{t+h|I_t}$ nicht mehr für alle Haushaltsjahre $h = 1, ..., 5$ berechnet werden. Die resultierenden Szenarien $\hat{Y}_i^{EA}$ als Eingangsreihen für die Potentialschätzung enden dann entsprechend vor dem Ende des Mittelfristzeitraumes. So ist zum einen sichergestellt, dass bei der ohnehin limitierten Echtzeitdatenbasis alle verfügbaren historischen Fehler Berücksichtigung finden. Zum anderen müssen die Szenarien bei fehlenden Prognosefehler $e_{t+h|I_t}$ früher enden um eine Verzerrung durch Vorwärts- und Rückwärtsglättung bspw. im Rahmen der Potentialschätzung nach Gleichung (4.11) zu verhindern.

[22] Dies ist der Fall, da die Berechnungen der Produktionslücke, der Konjunkturkomponente und damit letztlich der Kreditobergrenze nur noch deterministischer Natur sind.

[23] Hier kommen zumeist ARIMA Modelle zum Einsatz (vgl. z.B. Box et al., 2008).

beitslosenquote, der Arbeitszeit je Erwerbstätigen, der Arbeitnehmerentgelte sowie des Deflators des privaten Konsums.[24] Diese für das EU Verfahren ebenfalls notwendigen Daten haben wir der Veröffentlichung der Frühjahrsprojektion 2015 des BMWi entnommen.[25] Damit sind diese Inputdaten identisch zu der verwendeten Datenbasis der Bundesregierung zur Potentialschätzung des Frühjahres 2015.[26] Um zu einer Beurteilung der Unsicherheit der Potentialschätzung durch Revisionen des deutschen BIP zu kommen wurden alle weiteren Inputgrößen für alle Szenarien konstant gehalten. Die hier zu evaluierenden Verfahren arbeiten dabei zunächst mit realen BIP Daten. Alle im folgenden Kapitel vorgestellten Ergebnisse wurden allerdings in das Nominal überführt.

4.4 Empirische Ergebnisse

Um die Auswirkungen einer sich mit zunehmendem Informationsstand verändernden BIP Grundlage auf das zukünftige Produktionspotential aufzuzeigen haben wir zunächst BIP Szenarien für den aktuellen Prognosezeitraum der Mittelfrist von 2015 bis 2019 berechnet. Diese Szenarien dienen dann als Input für die hier betrachteten konkurrierenden potentialgebenden Verfahren der EU Kommission.

Die hieraus resultierenden Potentialszenarien des Produktionsfunktionsansatzes der EU Kommission für den Zeitraum 1980 bis 2019 finden sich in Abbildung 2. Die Potentialszenarien nach dem HP Filter in der Spezifikation der EU Kommission sind in Abbildung 3 dargestellt. Wie zu erwarten führen die am aktuellen Datenrand berücksichtigten historischen Prognose- und Revisionsfehler auch nach einer Glättung im Zuge der Potentialschätzung zu Abweichungen in den Potentialszenarien im Vergleich zur Potentialschätzung auf Grundlage der aktuellen BIP Projektionen der Bundesregierung. Mit Ausnahme des Szenarios basierend auf dem Datenstand des Frühjahres 2008 verlaufen die geschätzten Potentialszenarien dabei ausnahmslos oberhalb des Potentialpfades wie er sich aus dem aktuellen Datenstand des Frühjahres 2015 ergibt. Dies ist damit zu begründen, dass positive Revisions- und Prognosefehler des BIP auch zu positiven Prognosefehlern des Potentials führen und im betrachteten Zeitraum die hier verwendeten Frühjahrsprognosen im Mittel als eher konservativ zu bezeichnen sind.[27] Dies steht in Kontrast zu den Befunden in Kastrop und Snelting (2008), die noch von eher optimistischen Prognosen der Bundesregierung für den Zeitraum 2000 bis 2007 berichten. Sowohl der HP Filter als auch der Produktionsfunktionsansatz der EU Kommission führen

[24] Zur Erstellung von Szenariorechnungen stellt die EU Kommission ein spezielles "Conv tool" zur Verfügung. Für die Berechnungen in dieser Arbeit haben wir die Version des Frühjahrs 2015 verwendet und damit die aktuell verwendete Programmversion evaluiert.

[25] "Gesamtwirtschaftliches Produktionspotential und Konjunkturkomponenten" Datengrundlagen und Ergebnisse der Schätzungen der Bundesregierung. Stand: Frühjahrsprojektion 22.04.2015.

[26] Geringe Abweichungen in den Ergebnissen erklären sich durch Rundung der Inputs auf eine Nachkommastelle in den Veröffentlichungen der Bundesregierung. Zudem verwendet das BMWi eine "Gap-closure rule" zum Ende des mittelfristigen Finanzplanungszeitraumes, die im Ansatz der EU Kommission und damit in der vorliegenden Arbeit zunächst nicht berücksichtigt ist.

[27] Ein positiver Prognosefehler ist dabei gleichbedeutend mit einer Unterschätzung des BIP bzw. Potentialverlaufs. Der mittlere Prognose- bzw. Revisionsfehler des BIP für die Haushaltsjahre der Finanzplanung $h = 1, ..., 5$ ist auch nochmal nummerisch in Tabelle 3 dargestellt.

dabei zunächst zu qualitativ vergleichbaren Resultaten, was den Effekt der hier verwendeten Prognosefehler und Datenrevisionen auf die Potentialschätzung angeht.
Darüber hinaus stellt Abbildung 4 die Punktschätzungen des Produktionspotentials nach der EU Methode sowie nach dem HP Filter auf Basis des aktuellen Datenstandes[28] noch einmal zusammen grafisch dar. Wie aus der Abbildung ersichtlich, führen beide Verfahren auf vergleichbare Ergebnisse, insbesondere was die Höhe des ausgewiesenen Produktionspotentials angeht. Dieses Ergebnis stimmt mit den Befunden des SVR überein, der ebenfalls keine großen Unterschiede in der Potentialabschätzung anhand des HP Filters und produktionstheoretischer Verfahren erkennen kann (vgl. SVR, 2007, S.136).
Tabelle 1 stellt die Ergebnisse der Potential und Produktionslückenschätzung nummerisch dar. Betrachtet man die Produktionslückenschätzungen des EU Verfahrens und des HP Filters in den Spalten 3 und 5 über den Zeitraum 1980 bis 2014, kommen die beiden Verfahren ebenfalls zu sehr vergleichbaren Ergebnissen sowohl was das Vorzeichen der Produktionslücke als auch was die absolute Höhe betrifft. Allerdings ändert sich dies im Prognosezeitraum, d.h. im für die mittelfristige Haushaltsplanung relevanten Zeitraum. Hier diagnostizieren beide Verfahren teils unterschiedliche Vorzeichen der Produktionslücke mit entsprechenden Implikationen für die verfahrensspezifischen Konjunkturkomponenten. Darüber hinaus fällt auf, dass die Produktionslücken des EU Verfahrens in diesem Zeitraum absolut gesehen höher ausfallen als beim HP Filterverfahren.
Um die Planungssicherheit der Verfahren zu quantifizieren, haben wir entsprechende Unsicherheitsmaße für verschiedene Prognosehorizonte (h) beginnend mit dem laufenden Haushaltsjahr $h = 1, ..., 5$ ermittelt um die Auswirkungen statistischer Revisionen und Prognosefehler des BIP auf die Konjunkturkomponente und damit auf die mittelfristige Finanzplanung der öffentlichen Hand zu evaluieren. Trotz der im Untersuchungszeitraum als zu pessimistisch einzuschätzenden BIP Prognosen sind wir im Folgenden von asymptotisch unverzerrten, symmetrisch verteilten Prognose- bzw. Revisionsfehlern ausgegangen.
Die Ergebnisse über die verfahrensspezifischen Unsicherheiten haben wir in sogenannten Fancharts grafisch dargestellt, wobei Abbildung 5 den Fanchart des Produktionsfunktionsansatzes der EU Kommission und Abbildung 6 den Fanchart des HP Filters präsentiert. Fancharts bilden dabei verschiedene Risikoszenarien für das Produktionspotential und damit letztlich für die Haushaltsbudgets der öffentlichen Hand grafisch ab. Diese werden in der Politikberatung bisher im Bereich der Inflationsprognose zum Beispiel von der Bank von England eingesetzt (vgl. Britton et al., 1998). Vergleicht man Abbildung 5 und 6 fällt zunächst auf, dass wie zu erwarten die Prognoseunsicherheit σ_h der Potentialschätzungen beider Verfahren mit zunehmendem Prognosehorizont (h) anwachsen.
Tabelle 2 stellt die Standardabweichungen in der Mittelfristprognose der Verfahren gegenüber. Im laufenden Haushaltsjahr weist dabei der Produktionsfunktionsansatz mit 61,11 Mrd. Euro im Vergleich zum HP Filterverfahren mit 67,38 Mrd. Euro eine geringere Prognoseunsicherheit auf und ist damit prinzipiell besser geeignet das Produktionspotential des laufenden Jahres abzuschätzen. Ab dem kommenden Haushaltsjahr bis zum Ende der Mittelfristprojektionen weist dann allerdings der HP Filter die höhere Schätz- und Prognosegenauigkeit auf. Die sich

[28] Hier des Frühjahres 2015

hier ergebenden Differenzen sind dabei nicht unerheblich. So haben wir für das kommende und daher planungsrelevante Haushaltsjahr eine um circa 8 Mrd. Euro geringere Standardabweichung des methodisch relativ simplen HP Filters im Vergleich zum theoriefundierten Ansatz der EU Kommission ermittelt. Die Differenz in den Standardabweichungen wächst zudem mit dem Prognosehorizont weiter an, sodass zum Ende des mittelfristigen Finanzplanungszeitraums eine um 30,1 Mrd. Euro höhere Standardabweichung der Potentialprognose des Produktionsfunktionsansatzes der EU Kommission im Vergleich zum HP Filter ausgewiesen wird.
Tabelle 3 stellt noch einmal den mittleren Revisonsfehler sowie die Standardabweichung der Jahr zu Jahr Revisionen des nominalen Bruttoinlandsproduktes für die Haushaltsjahre $h = 1, ..., 5$ dar.[29] Vergleicht man die Standardabweichung der Jahr zu Jahr Revisionen des nominalen Bruttoinlandsproduktes aus Tabelle 3 mit der Standardabweichung der Potentialprognose aus Tabelle 2 fällt zunächst auf, dass letztere für den HP Filter über alle Prognosehorizonte kleiner ausfallen als die Standardabweichungen der BIP Revisionen ansich. Dieses Ergebnis ist zu erwarten, da die Glättung im Rahmen des HP Filters nach Gleichung (4.11) zu einer geringeren Variation der Potentialreihe im Vergleich zur Reihe des Bruttoinlandsproduktes führt. Für die Potentialschätzung anhand der EU Methode ergibt sich allerdings ein anderes Bild. Vergleicht man hier die Jahr zu Jahr Revisionen des BIP mit der Standardabweichung der Potentialprognose zeigt sich, dass die BIP Revisionen ab einem $h \geq 4$ zu einer höheren Standardabweichung der Potentialprognose mit entsprechenden Implikationen für die Trendstabilität führen. Dieser Befund steht dabei in Einklang mit der höheren Persistenz des Produktionslückenverlaufes wie er aus Tabelle 1 ersichtlich wurde. Dennoch zeigt sich hier, dass Revisionen des BIP als maßgebliche Eingangsgröße der Potentialschätzung bei Verwendung des Produktionsfunktionsansatz der EU Kommission zum Ende der Mittelfrist zu einem überproportionalen Revisionsbedarf des Produktionspotentials führen können.
Wie bereits in Kapitel 4.2 beschrieben dient die Schätzung des zukünftigen Produktionspotentials der Ermittlung der Konjunkturkomponente im Rahmen der Bundesmethode. Nach der Schätzung des Potentials wird diese in zwei deterministischen Schritten über die Produktionslücke als Abweichung von BIP und Potential berechnet.[30] Die statistische Unsicherheit entsteht dementsprechend maßgeblich durch die Schätzung des Produktionspotentials an sich. Da es für die Entscheidungsfindung im politischen Prozess aber unerlässlich erscheint Aussagen über die Unsicherheit der Produktionslücke zu treffen präsentieren wir hier auch entsprechende Ergebnisse unter der Annahme, dass es sich bei der zugrunde liegenden aktuellen Ist- und Solldatenbasis des BIP um feste Größen der Finanzplanung handelt.
Die Abbildungen 7 und 8 geben zunächst einen visuellen Eindruck der Produktionslückenszenarien wie sie sich aus der Unsicherheit über die Potentialschätzung ergeben. Analog zu den Potentialszenarien in den Abbildungen 5 und 6 fällt zunächst auf, dass die historischen Prognosefehler des BIP, bis auf den Datenstand des Frühjahres 2008, im Vergleich zur Produktionslücke auf Basis des aktuellen Datenstandes zu einer negativeren Produktionslücke am

[29] Die Jahr zu Jahr Revisionen wurden dabei nach Gleichung 4.12 berechnet und in das Nominal überführt.
[30] Die so ermittelte Produktionslücke wird dann wie bereits in Kapitel 4.2 beschrieben mit der Budgetsensitivität multipliziert um die Konjunkturkomponente zu erhalten.

aktuellen Datenrand führen. Abgesehen vom Frühjahr 2008 mit seinen weit zu optimistischen Prognosen über die zukünftige BIP Entwicklung kommt es außerdem zu keinen Vorzeichenwechseln über die betrachteten Szenarien. Zudem führt eine Unterschätzung des BIP Verlaufs auch zu einer Unterschätzung der Strukturkomponente. Dementsprechend führen die konservativen BIP Prognosen der letzten Jahre verfahrensunabhängig eher auf einen Konsolidierungskurs denn zu einer Verletzung der langfristigen Ziele der Schuldenbremse.
Dies kann als Evidenz dafür gesehen werden, dass die Bundesregierung im Zeitraum von 2005 bis 2015 anders als von der Verfassung gefordert das Nettoneuverschuldungsverbot nicht langfristig, d.h. im Mittel über den Konjunkturzyklus hinweg, sondern in jedem einzelnen Haushaltsjahr erfüllt hat. Kritiker der Schuldenbremse argumentieren dies könne zu einer dauerhaft zu niedrigen Investitionsquote führen (vgl. Bofinger und Horn, 2009). Dieses Risiko besteht auch durch dauerhaft zu pessimistische BIP Prognosen als Grundlage für die Potentialschätzung.
Abbildung 9 und 10 stellen die Abschätzung der Prognoseunsicherheit über die Produktionslücke nach dem Verfahren der EU Kommission sowie nach dem HP Filterverfahren als Fancharts dar. Unter den hier getroffenen Annahmen ergibt sich dann analog zu den Fancharts des Produktionspotentials ein symmetrischer Unsicherheitsbereich, welcher einen Vorzeichenwechsel der Produktionslücke für beide Verfahren mit einschließt.[31] Dennoch zeigt sich auch für die Outputlücken, dass der HP Filter im Vergleich zum Produktionsfunktionsansatz ab dem kommenden Haushaltsjahr die geringere Schätzunsicherheit aufweist und daher seine Verwendung auch mit einer höheren Planungssicherheit für die Budgets der öffentlichen Hand einhergehen würde.

4.5 Zusammenfassung und Schlussfolgerung

Die hier vorgestellten Ergebnisse geben Evidenz, dass die verwendeten BIP Prognosen erheblichen Einfluss auf die Potential- und Produktionslückenabschätzung, wie sie im Zuge der Haushalts- und Finanzplanung regelmäßig nötig sind, haben. Die Prognosen der Bundesregierung sind im Beobachtungszeitraum zwischen 2005 und 2015 im Mittel als konservativ zu bezeichnen, da die tatsächliche bzw. ex post bekannte Entwicklung des Bruttoinlandsproduktes systematisch unterschätzt wurde. So hat eine Berücksichtigung historischer Revisionen und Prognosefehler am aktuellen Datenrand verfahrensunabhängig ex ante zu einer Unterschätzung der langfristigen Produktionskapazitäten der deutschen Volkswirtschaft im Vergleich zu (fast) allen Szenarien geführt. Zudem hat sich gezeigt, dass die qualitativen Auswirkungen von BIP Revisionen sowie Verlauf und Höhe des Produktionspotentials weitestgehend verfahrensunabhängig von der hier evaluierten Methodik zur Bestimmung des Produktionspotentials sind.
Wie aus den erstellten Produktionslückenszenarien ersichtlich, wäre bei Berücksichtigung des

[31] Es sei an dieser Stelle nochmals darauf hingewiesen, dass unverzerrte, symmetrisch verteilte Prognosefehler mit einem Erwartungswert von Null eine Einhaltung der Schuldenbremse suggerieren, da sich kurzfristige Abweichungen langfristig wieder ausgleichen und die Schuldenbremse das Ziel einer langfristigen Nettoneuverschuldung von Null verfolgt.

ex post bekannten, tatsächlichen BIP Verlaufs verfahrensunabhängig eine größere Produktionslücke und daher eine größere Konjunkturkomponente der Nettokreditaufnahme möglich gewesen. Da die BIP Prognosen der Bundesregierung zudem direkten Einfluss auf die Höhe der Strukturkomponente der zulässigen Nettokreditaufnahme haben, führen diese Befunde im Beobachtungszeitraum verfahrensunabhängig eher auf einen Konsolidierungskurs denn zu einer Verletzung der Schuldenbremse.

Im Hinblick auf die Planungssicherheit der Haushaltsbudgets des Bundes, welche wir anhand der historischen Prognoseunsicherheit des Potentials und der Produktionslücke auch quantitativ evaluiert haben, zeigt sich allerdings, dass der HP Filter bereits ab dem kommenden Haushaltsjahr eine verfahrensspezifische, höhere Planungssicherheit beziehungsweise eine geringere Schätz- und Prognoseunsicherheit für Produktionspotential und -Lücke aufweist. Der weitest gehende Gleichlauf des Potentials basierend auf den in dieser Studie evaluierten Verfahren lässt zudem wenig Spielraum um eine Vorteilhaftigkeit der EU Methode bezüglich einer verbesserten antizyklischen Ausgabenpolitik zu erkennen. Da der HP Filter des Weiteren auch das Kriterium einer transparenten, leicht nachvollziehbaren und daher glaubhaften Schuldenregel erfüllt, stellt er auch weiterhin eine plausible Alternative zum theorie-fundierten Produktionsfunktionsansatz der EU Kommission dar.

Für eine abschließende Beurteilung der hier evaluierten Verfahren wären jedoch ergänzende Untersuchungen auf Basis einer erweiterten Datenbasis wünschenswert. Zudem wäre eine zeitliche Festlegung abgeschlossener Konjunkturzyklen im Untersuchungszeitraum hilfreich, die aber erst ex post mit einigem zeitlichen Abstand erfolgen kann.

4.6 Bibliographie

Berberich, U. (2012). Steuerschätzung und Analyse der Prognosegüte für die Bundesrepublik Deutschland. Dissertation, Universität Hohenheim.

Bundesministerium der Finanzen und Bundesministerium für Wirtschaft und Energie (2015), "Gesamtwirtschaftliches Produktionspotential und Konjunkturkomponenten", Stand: Frühjahrsprojektion 22.04.2015.

Bofinger, P. und G. Horn (2009). Die Schuldenbremse gefährdet die gesamtwirtschaftliche Stabilität und die Zukunft unserer Kinder. Appell an die Mitglieder von Bundestag und Bundesrat vom 25.05.2009, zuletzt abgerufen am 26.09.2014 unter: http://www.boeckler.de/pdf/imk_appell_schuldenbremse.pdf

Box, E. Jenkins, G. und G. Reinsel (2008). Time Series Analysis: Forecasting and Control, 4. Auflage. Wiley, New Jersey.

Boysen-Hogrefe, J. und M. Haas (2014). Konjunkturbereinigung für den Haushalt des Landes Schleswig-Holstein: Es besteht Handlungsbedarf! Ifw Fokus 162.

Boysen-Hogrefe, J. Haas, M. und S. Müller (2014). Abschätzung von Bandbreiten als Risikoszenarien für die Entwicklung des Trendsteuerpfades. Gutachten im Auftrag des Finanzministeriums Schleswig-Holstein.

Britton, E., P. Fisher und J. Whitley (1998). The Inflation Report Projections: Understanding the Fan Chart. Bank of England Quarterly Bulletin (February).

Bruchez, P.-A. (2003). A Modification of the HP Filter Aiming at Reducing the End-Point Bias. Eidg. Finanzverwaltung, Working Paper.

Burret, H.T. (2013). Die deutsche Schuldenbremse als Allheilmittel - eine Analyse im historischen Kontext. Journal für Generationengerechtigkeit 13, 48-65.

BMF (2015). Ergebnisse der Sitzungen des Arbeitskreises Steuerschätzungen 2001 bis 2014. Zuletzt abgerufen am 19.05.2016, unter: http://www.bundesfinanzministerium.de/Content/DE/Standardartikel/Themen/Steuern/Steuerschaetzungen_und_Steuereinnahmen/Steuerschaetzung/ergebnisse-des-arbeitskreises-steuerschaetzungen-seit-1971.html

Colombier, C. (2004). Eine Neubewertung der Schuldenbremse. Eidg. Finanzverwaltung, Working Paper No. 2.

D'Auria, F., C. Denis, K. Havik, K. Mc Morrow, C.Planas, R. Raciborski, W. Röger und A. Rossi (2010). The production function methodology for calculating potential growth rates and output gaps. European Commission, Economic Papers 420.

Europäische Kommission (2015). Programme, Dokumentationen und Echtzeitdaten zur Potentialschätzung. Zuletzt abgerufen am 19.05.2016, unter: https://circabc.europa.eu/

Gesetz zur Förderung der Stabilität und des Wachstums der Wirtschaft (StabG), 1967, zuletzt abgerufen am 19.05.2016, unter:
http://www.bgbl.de/xaver/bgbl/start.xav?startbk=Bundesanzeiger_BGBl&jumpTo=bgbl167s0582.pdf#___bgbl___% 2F % 2F*[%40attr_id%3D%27bgbl167s0582.pdf%27]___1463649545130

Grundgesetz für die Bundesrepublik Deutschland, zuletzt geändert am 11.07.2012, zuletzt abgerufen am 26.09.2014, unter:
https://www.bundestag.de/bundestag/aufgaben/rechtsgrundlagen/grundgesetz/gg/245216

Girouard, N. und C. Andre (2005). Measuring Cyclically-Adjusted Budget Balances for OECD Countries, OECD Economics Department Working Papers 434.

Haas, M. und S. Müller (2012). Evaluierung und Weiterentwicklung der Methodik der Ermittlung des Trendsteuerpfades und der Fortschreibung des Trendsteuerpfades (Konjunkturbereinigungsverfahren). Gutachten im Auftrag des Finanzministeriums Schleswig-Holstein.

Hamilton, J. (1994). Time Series Analysis. Princeton University Press: Princeton.

Havik, K. Mc Morrow, K. Orlandi, F. Planas, C. Raciborski, R. Röger, W. Rossi, A. Thum-Thysen, A. und V. Vandermeulen (2014). The production function methodology for calculating potential growth rates and output gaps. European Commission, Economic Papers 535.

Holtemöller, O., M. Altemeyer-Bartscher, K. Drechsel, S. Freye und G. Zeddies (2014). Modelle zur Konjunkturbereinigung und deren Auswirkungen. Kurzgutachten im Auftrag des Landesrechnungshofs Mecklenburg-Vorpommern

Hodrick, E. und E. Prescott (1997). Postwar US Business Cycles: An Empirical Investigation. Journal of Money, Credit and Banking 29, 1-16.

Kastrop, Ch. und M. Snelting (2008). Das Modell des Bundesfinanzministeriums für eine neue Schuldenregel. Wirtschaftsdienst 88, 375-382.

Kydland, F. und E. Prescott (1990). Business Cycles: Real Facts and a Monetary Myth. Federal Reserve Bank of Minneapolis Quarterly Journal, 3-18.

Leser, C. E. V. (1961). A Simple Method of Trend Construction. Journal of the Royal Statistical Society. Series B (Methodological), 23(1), 91-107.

Mills, T.C. (2003). Modelling trends and Cycles in Economic Time Series. Palgrave Macmillan, Houndmills.

Mourre, G. Astarita, C. und S. Princen (2014). Adjusting the budget balance for the business cycle: the EU methodology. European Commission, European Economy, Economic Papers 536.

Mourre, G. Isbasoiu, G. Paternoster, D. und M. Salto (2013). The cyclically-adjusted budget balance used in the EU fiscal framework: an update. European Commission, European Economy, Economic Papers 478.

Orlandi, F. (2012), Structural unemployment and its determinants in the EU countries, European Commission, European Economy Economic Paper, No 455.

Sachverständigenrat zur Begutachtung der gesamtwirtschaftlichen Entwicklung (2003). "Jahresgutachten 2003/04: Staatsfinanzen konsolidieren - Steuersystem reformieren", zuletzt abgerufen am 26.09.2014, unter:
http://www.sachverstaendigenrat-wirtschaft.de/fileadmin/dateiablage/download/gutachten/03_ges.pdf

Sachverständigenrat zur Begutachtung der gesamtwirtschaftlichen Entwicklung (2007). "Staatsverschuldung wirksam begrenzen". Expertise im Auftrag des Bundesministers für Wirtschaft und Technologie, zuletzt abgerufen am 26.09.2014, unter:
http://www.sachverstaendigenrat-wirtschaft.de/fileadmin/dateiablage/Expertisen/Staatsverschuldung_wirksam_begrenzen.pdf

Schäuble, W. (2013). Das Altersvorsorgevermögen in Deutschland hat keine Schwindsucht. Interview mit der Versicherungswirtschaft, Nr. 6, vom 15.03.2013. 10-11.

Schlittgen, R. und B. Streitberg (1997). Zeitreihenanalyse, 7. Auflage. Oldenbourg, München.

Stamfort, S. (2005). Berechnung trendbereinigter Indikatoren für Deutschland mit Hilfe von Filterverfahren. Deutsche Bundesbank Diskussionspapier 19/2005, Reihe 1: Volkswirtschaftliche Studien.

Ravn, M. und H. Uhlig (2002). On Adjusting the HP-Filter for the Frequency of Observations. Review of Economics and Statistics, 84(2), 371-76.

4.7 Appendix: Tabellen und Abbildungen

Appendix A: Abbildungen

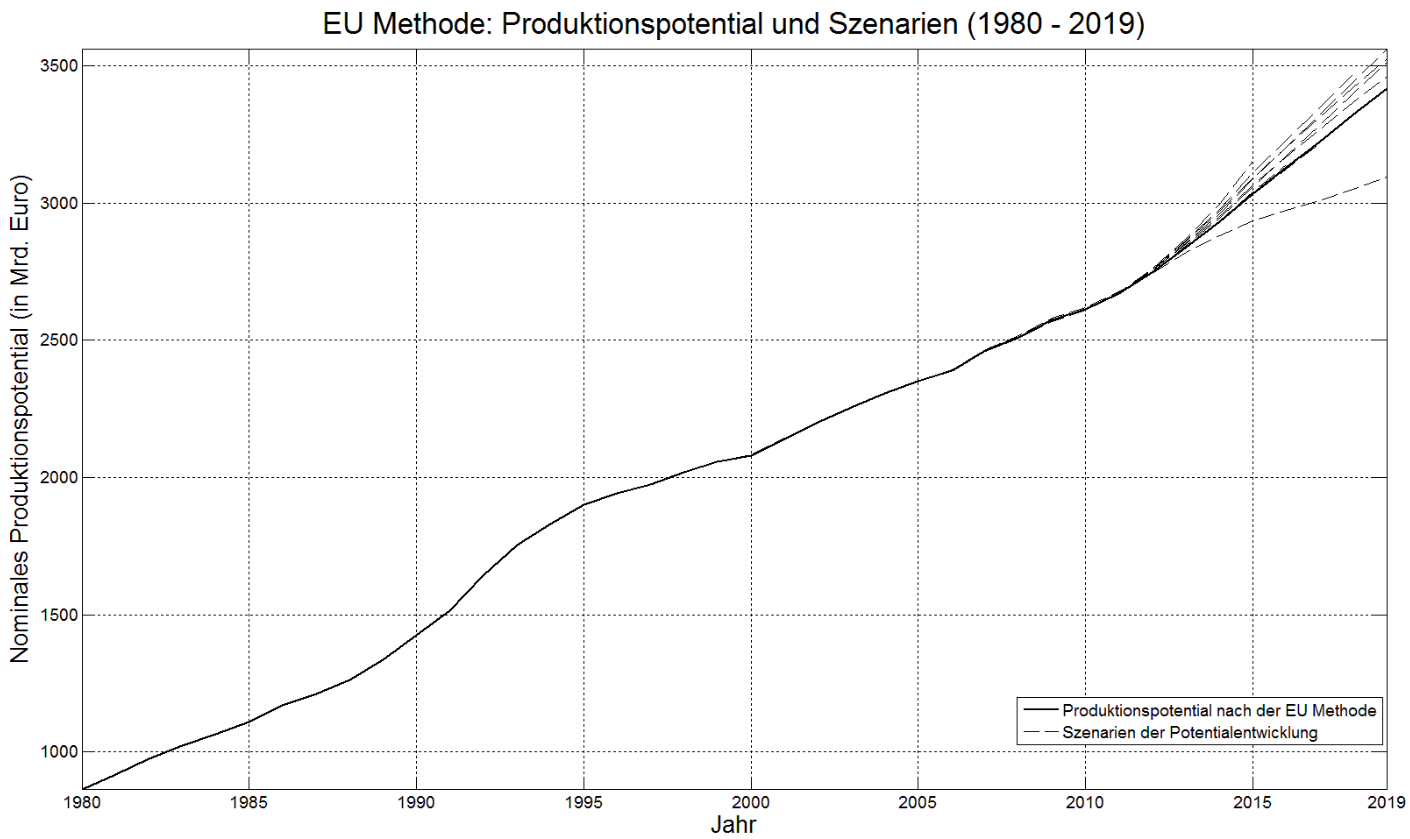

Abbildung 2: Entwicklung des nominalen Produktionspotentials (durchgezogene Linie) und Szenarien (unterbrochene Linien) für den Zeitraum 1980 - 2019 basierend auf Schätzungen des Produktionsfunktionsansatzes der EU Kommission.

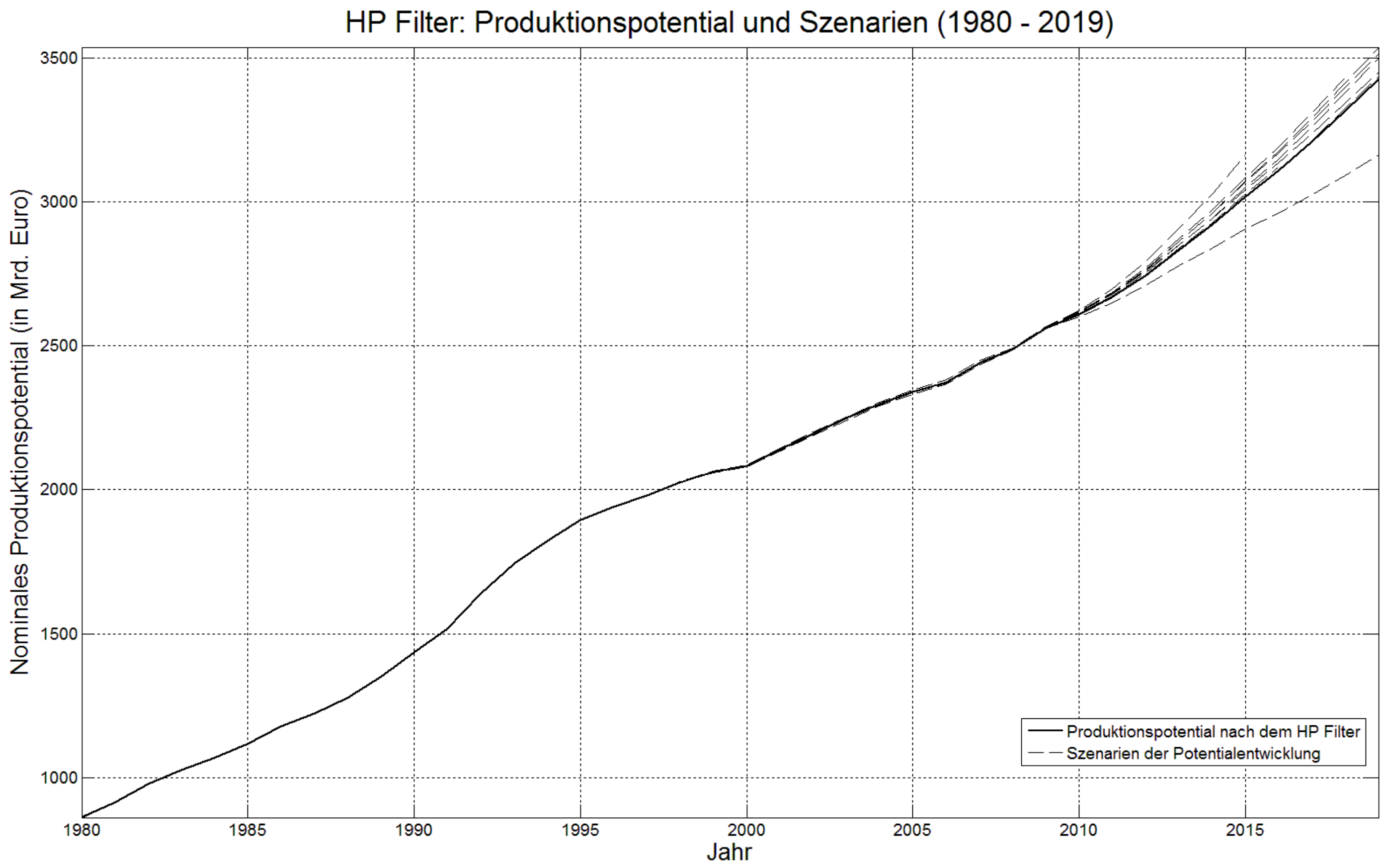

Abbildung 3: Entwicklung des nominalen Produktionspotentials (durchgezogene Linie) und Szenarien (unterbrochene Linien) für den Zeitraum 1980 - 2019 basierend auf Schätzungen anhand des HP Filters in der Spezifikation der EU Kommission.

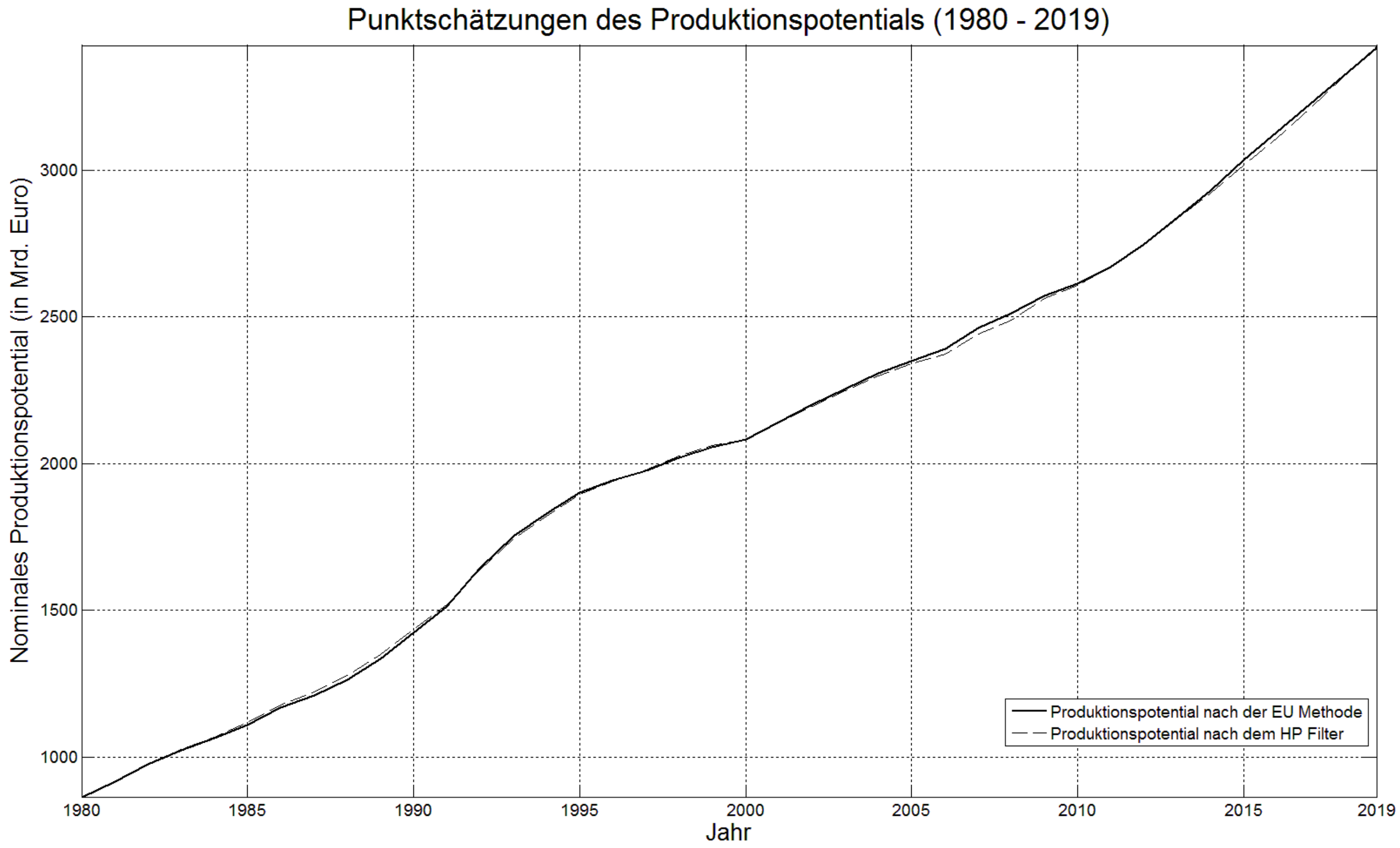

Abbildung 4: Entwicklung des nominalen Produktionspotentials nach der EU Methode (durchgezogene Linie) und dem HP Filter in der Spezifikation der EU Kommission (unterbrochene Linien) für den Zeitraum 1980 - 2019.

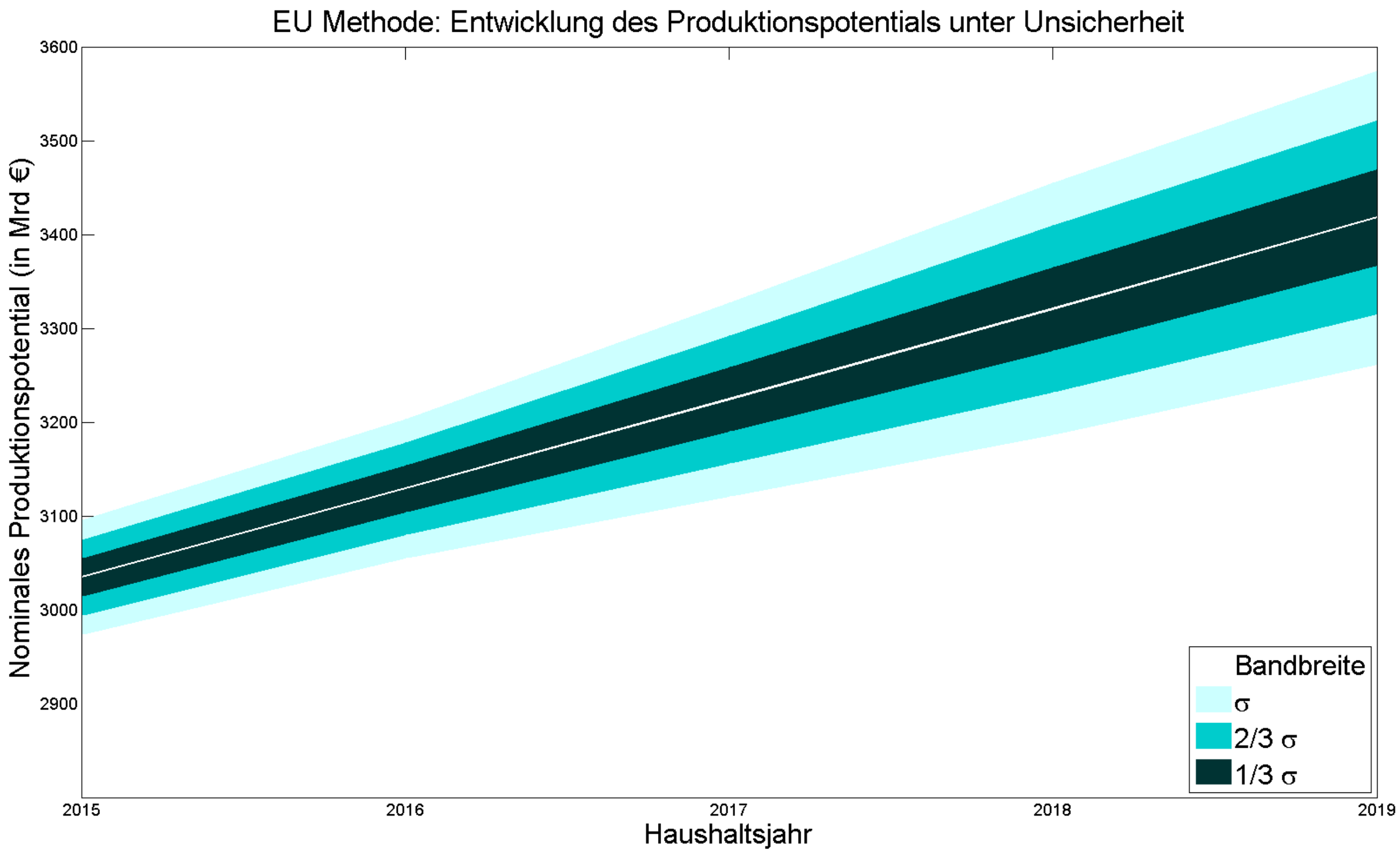

Abbildung 5: Punktschätzung des nominalen Produktionspotentials für den Prognosezeitraum 2015 – 2019 nach dem Produktionsfunktionsansatz der EU Kommission (weiße Linie) und Unsicherheitsbereiche (dunkel- bis hellblau) entsprechend einem Drittel, zwei Drittel und einer vollen Standardabweichung der Potentialprognose (σ_h).

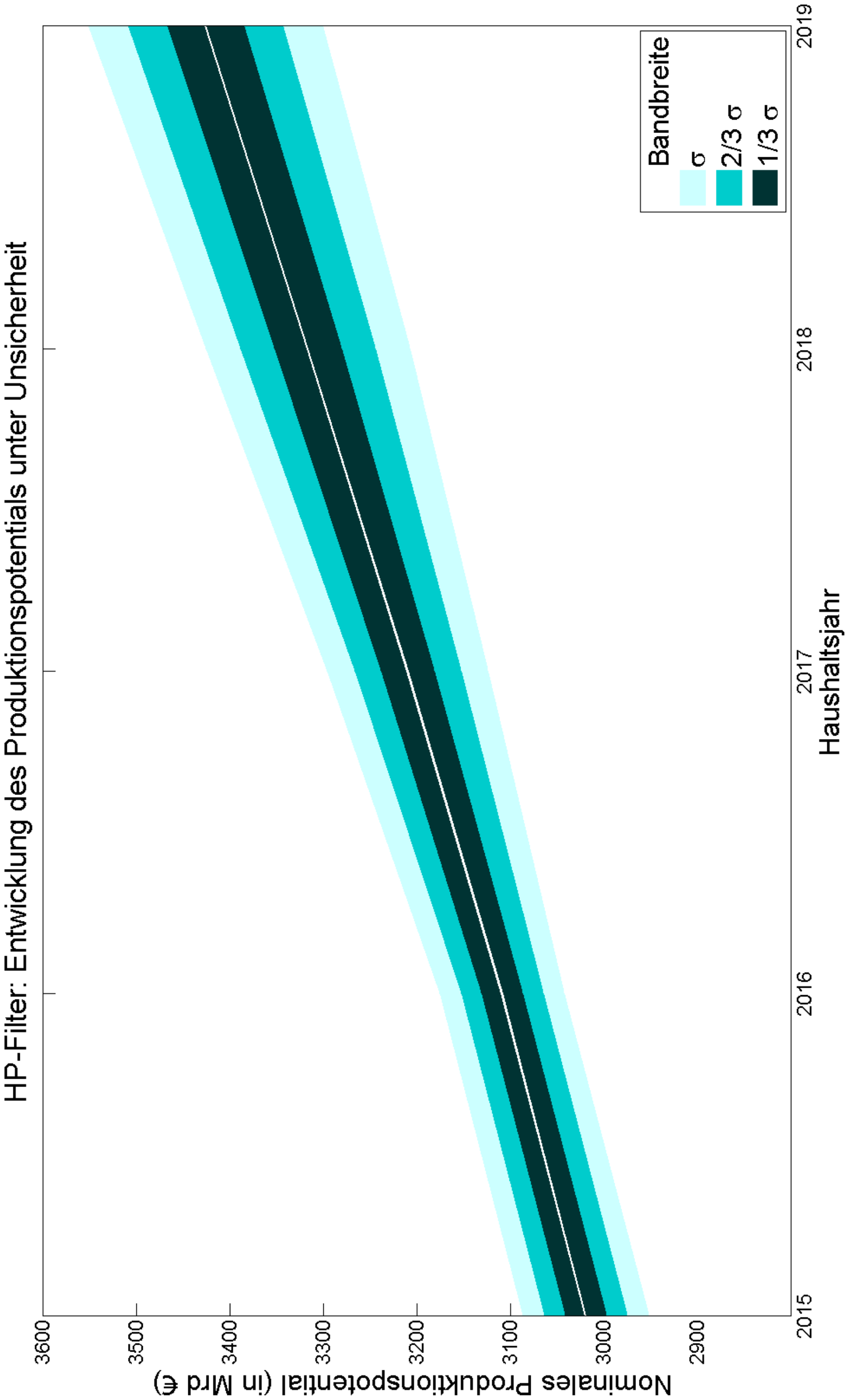

Abbildung 6: Punktschätzung des nominalen Produktionspotentials für den Prognosezeitraum 2015 - 2019 mit dem HP Filter in der Spezifikation der EU Kommission (weiße Linie) und Unsicherheitsbereiche (dunkel- bis hellblau) entsprechend einem Drittel, zwei Drittel und einer vollen Standardabweichung der Potentialprognose (σ_h).

Abbildung 7: Entwicklung der nominalen Produktionslücke (Linie) und Szenarien (Kreuze) für den Zeitraum 1980 - 2019 basierend auf einer Schätzung anhand des Produktionsfunktionsansatzes der EU Kommission.

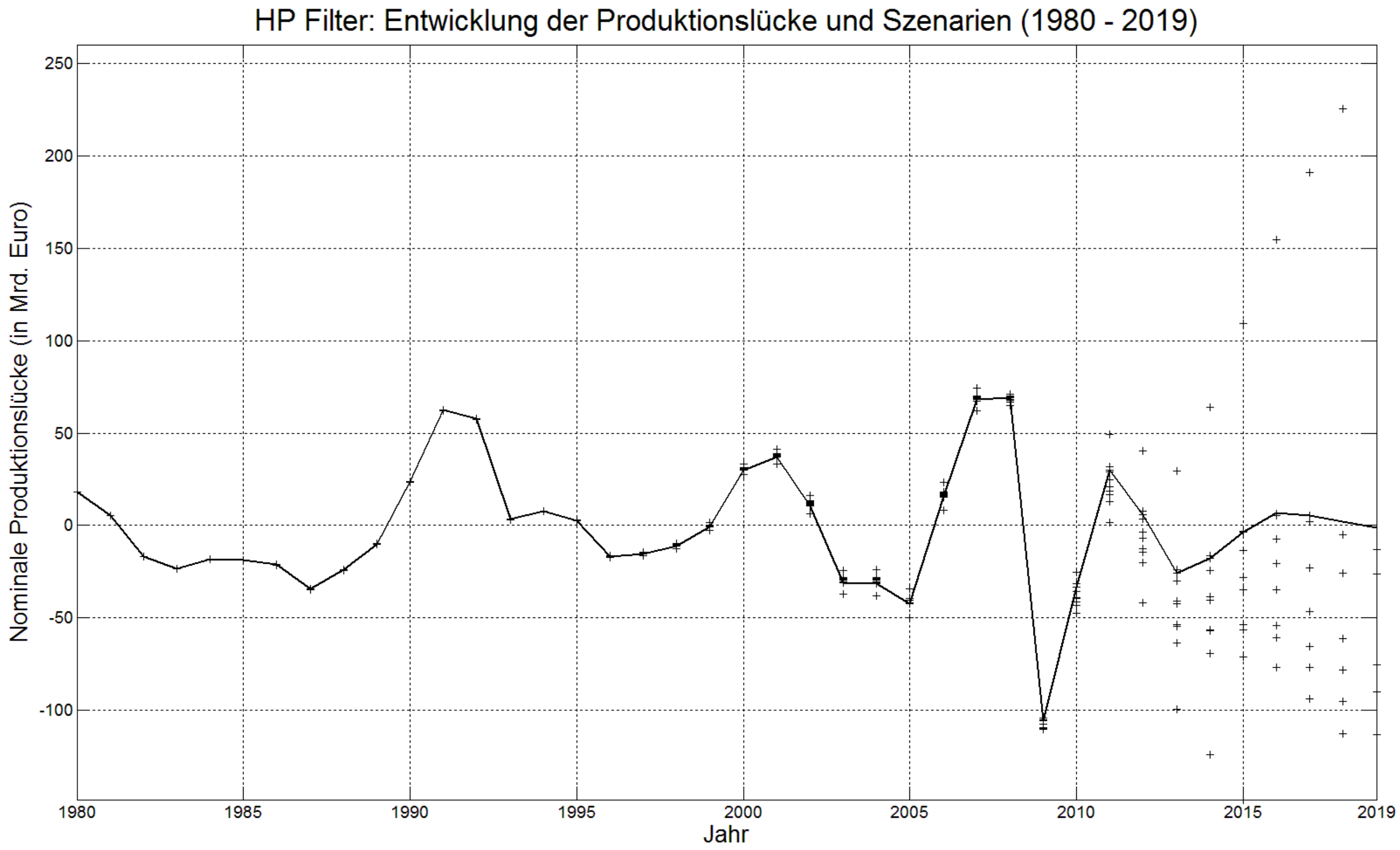

Abbildung 8: Entwicklung der nominalen Produktionslücke (Linie) und Szenarien (Kreuze) für den Zeitraum 1980 - 2019 basierend auf einer Schätzung anhand des HP Filters in der Spezifikation der EU Kommission.

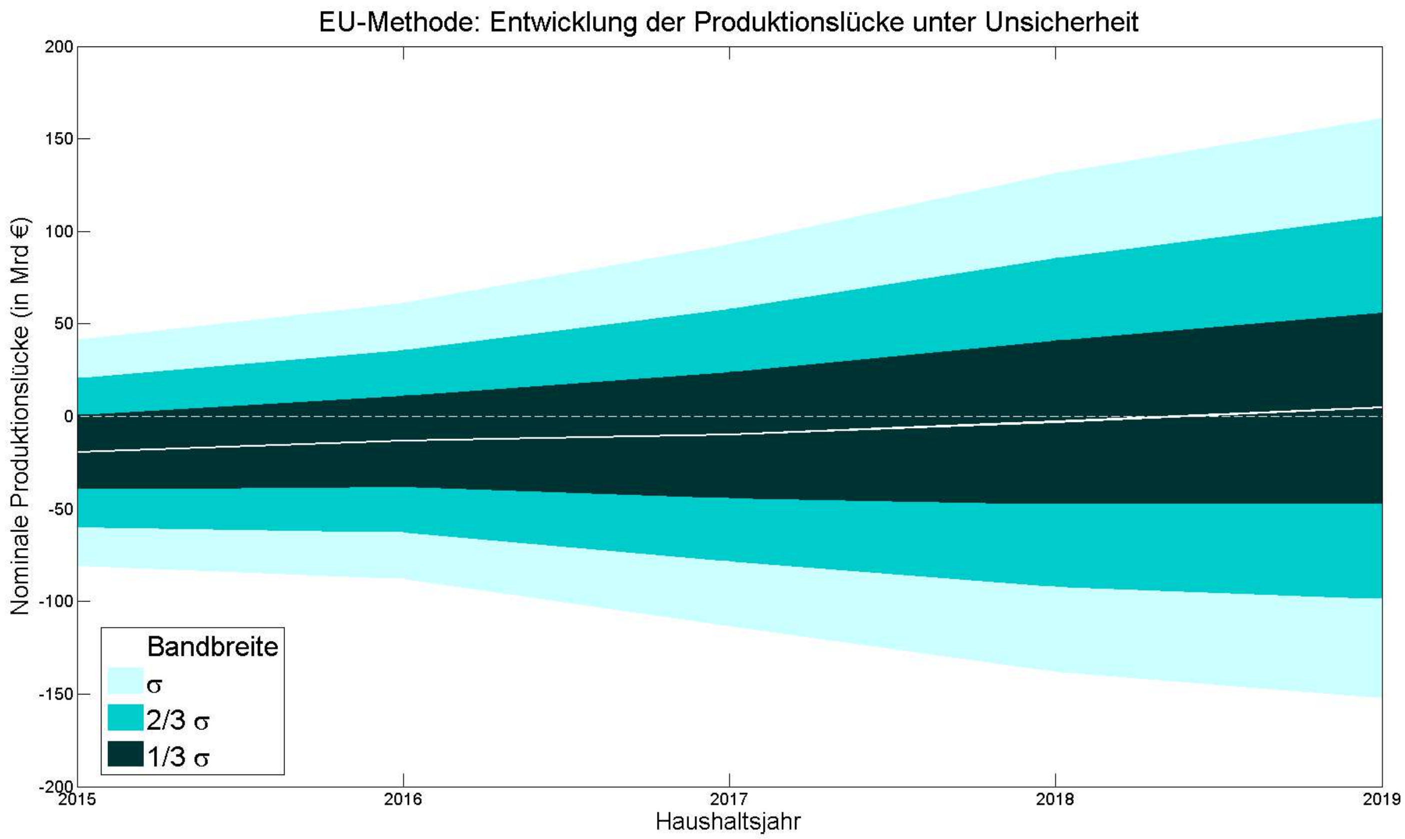

Abbildung 9: Punktschätzung der nominalen Produktionslücke (in Mrd. Euro) für den Prognosezeitraum 2015 - 2019 nach dem Produktionsfunktionsansatz der EU Kommission (weiß-durchgezogene Linie) und Unsicherheitsbereiche (dunkel- bis hellblau) entsprechend einem Drittel, zwei Drittel und einer vollen Standardabweichung der Potentialprognose (σ_h).

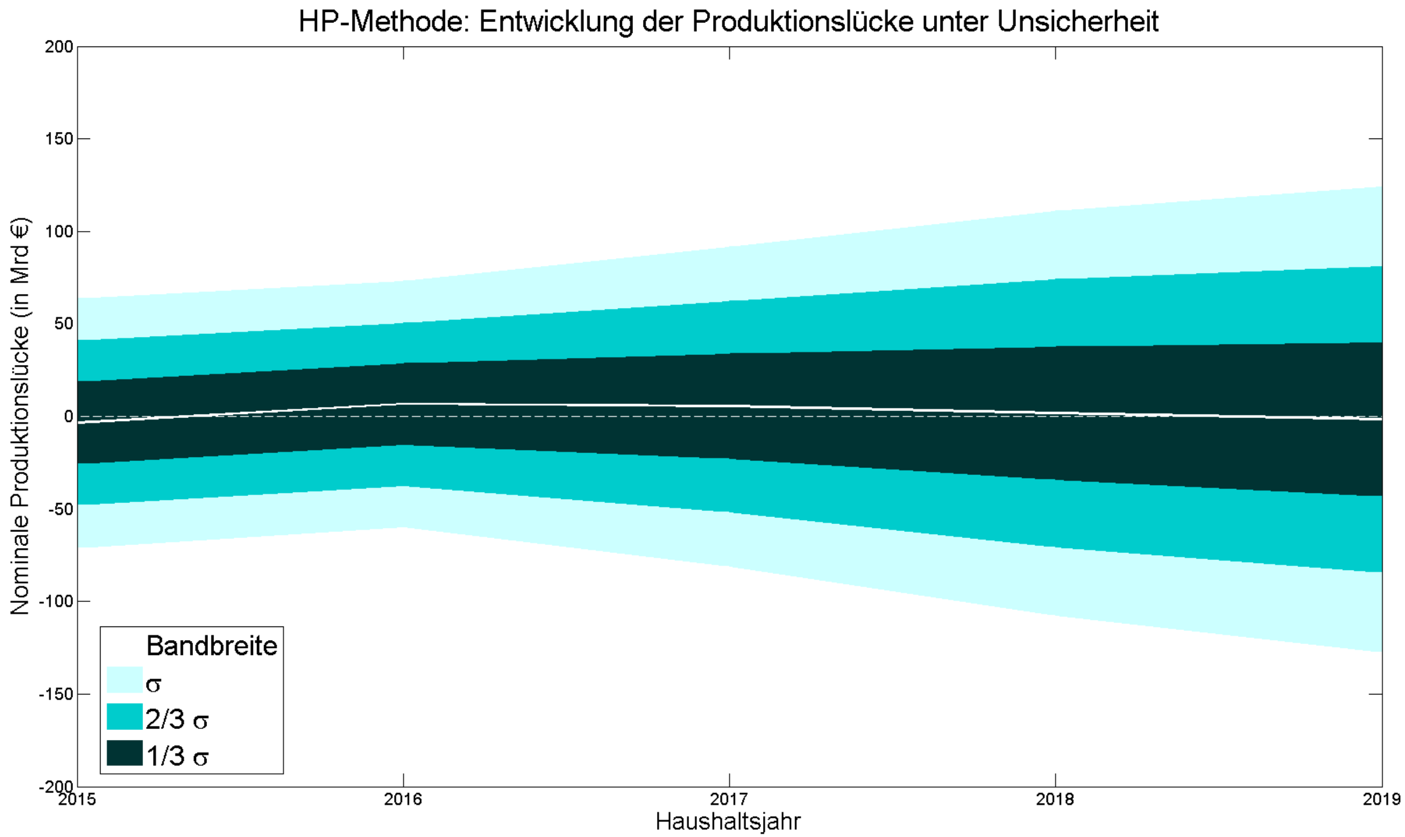

Abbildung 10: Punktschätzung der nominalen Produktionslücke (in Mrd. Euro) für den Prognosezeitraum 2015 - 2019 mit dem HP Filter in der Spezifikation der EU Kommission (weiß-durchgezogene Linie) und Unsicherheitsbereiche (dunkel- bis hellblau) entsprechend einem Drittel, zwei Drittel und einer vollen Standardabweichung der Potentialprognose (σ_h).

Appendix B: Tabellen

Jahr	Y	Y_{EU}^P	OG_{EU}	Y_{HP}^P	OG_{HP}
1980	879,32	861,45	17,87	861,65	17,67
1981	921,13	916,38	4,75	916,05	5,08
1982	959,13	975,53	-16,41	976,82	-17,70
1983	1002,40	1022,77	-20,37	1025,75	-23,35
1984	1051,63	1063,79	-12,16	1069,18	-17,54
1985	1099,19	1108,75	-9,57	1117,10	-17,92
1986	1158,04	1168,34	-10,30	1178,58	-20,54
1987	1187,95	1210,31	-22,36	1222,96	-35,00
1988	1253,27	1262,88	-9,62	1277,49	-24,22
1989	1338,93	1336,16	2,77	1349,73	-10,79
1990	1457,76	1424,85	32,91	1434,38	23,38
1991	1579,09	1513,41	65,68	1517,40	61,69
1992	1694,58	1642,63	51,95	1637,51	57,07
1993	1748,33	1754,67	-6,34	1745,25	3,08
1994	1831,29	1831,90	-0,62	1822,64	8,64
1995	1898,84	1901,14	-2,30	1895,47	3,37
1996	1924,47	1942,28	-17,81	1941,76	-17,29
1997	1963,99	1975,66	-11,67	1980,29	-16,29
1998	2016,10	2018,99	-2,89	2026,59	-10,49
1999	2060,74	2056,54	4,20	2062,72	-1,98
2000	2112,83	2081,44	31,39	2083,49	29,34
2001	2177,39	2142,08	35,31	2139,94	37,45
2002	2206,37	2200,29	6,09	2195,53	10,85
2003	2216,64	2255,00	-38,36	2248,33	-31,69
2004	2266,87	2308,02	-41,15	2298,94	-32,07
2005	2297,43	2351,39	-53,96	2340,26	-42,83
2006	2390,21	2391,05	-0,84	2374,56	15,64
2007	2509,89	2463,37	46,52	2441,66	68,23
2008	2557,28	2511,86	45,42	2488,82	68,46
2009	2457,65	2573,46	-115,81	2562,31	-104,66
2010	2576,22	2612,85	-36,63	2609,43	-33,21
2011	2698,06	2671,84	26,22	2669,04	29,03
2012	2751,08	2747,21	3,87	2744,07	7,01
2013	2810,30	2839,66	-29,35	2835,22	-24,91
2014	2904,43	2931,25	-26,82	2921,39	-16,96
2015	3015,24	3034,58	-19,34	3019,01	-3,77
2016	3116,05	3129,15	-13,10	3108,61	7,44
2017	3214,43	3224,35	-9,92	3209,54	4,89
2018	3317,76	3320,81	-3,05	3316,25	1,52
2019	3423,27	3418,43	4,84	3425,83	-2,56

Tabelle 1: Ergebnisse der nominalen Potential- und Produktionslückenschätzung nach der Methode der EU Kommission (Y_{EU}^P) und (OG_{EU}) sowie nach dem HP Filter in der Spezifikation der EU Kommission (Y_{HP}^P) und (OG_{HP}) respektive für den Zeitraum 1980 - 2019 basierend auf dem AMECO BIP Stand des Frühjahres 2015 (Y) in Mrd. Euro. Rote Markierungen stehen für den Zeitraum der aktuellen Mittelfristprojektionen des Frühjahres 2015.

h	σ_{EU}	σ_{HP}
1	61,11	67,38
2	74,48	66,52
3	103,08	86,36
4	134,53	109,46
5	156,57	125,78

Tabelle 2: Standardabweichungen der nominalen Potentialprognose nach dem EU Verfahren (σ_{EU}) und nach dem HP Filter (σ_{HP}) in Mrd. Euro für die Haushaltsjahre der Mittelfrist $h = 1, ..., 5$.

h	$\bar{e}_{t+h}$	σ_e
1	57,66	70,34
2	22,63	94,97
3	20,91	117,13
4	25,50	126,29
5	9,61	130,76

Tabelle 3: Mittlerer Jahr zu Jahr Revisionsbedarf des nominalen BIP ($\bar{e}_{t+h}$) und Standardabweichungen der BIP-Revisionen (σ_e) basierend auf den Projektionen des Arbeitskreises Steuerschätzungen in Mrd. Euro für die Haushaltsjahre der Mittelfrist $h = 1, ..., 5$.

Chapter 5

Evaluierung und Weiterentwicklung der Methodik der Ermittlung des Trendsteuerpfades und der Fortschreibung des Trendsteuerpfades (Konjunkturbereinigungsverfahren)

Im Auftrag des: Finanzministerium Schleswig-Holstein

Mitverfasst durch: Markus Haas

Abstract

Gegenstand dieser Arbeit ist die Entwicklung und Evaluation einer geeigneten Methodik zur Ermittlung des Trendsteuerpfades im Sinne der langfristig zu erwartenden Entwicklung des Steueraufkommens des Landes Schleswig-Holstein unter Berücksichtigung des geltenden Landes- und übergeordneten Bundesrechts. Die Prognose der langfristigen Steuerentwicklung ist die entscheidende Größe bei der Ermittlung und Fortschreibung der Einnahmeseite des Landeshaushalts im Zuge der mittelfristigen Haushaltsplanung. Ab 2020 haben sich die Länder dabei im Rahmen der Schuldenbremse verpflichtet, ausgabenseitig eine strukturelle, das heißt konjunkturbereinigte Neuverschuldung von Null zu erreichen. Zudem findet über die Koppelung der Landesausgaben an den langfristigen Einnahmetrend eine Glättung der Ausgaben über die Zeit statt, die dazu beiträgt, unerwünschte, konjunkturbedingte Finanzierungslücken zu vermeiden. Zur Evaluation verschiedener geeigneter Verfahren zur Bestimmung des langfristigen Steueraufkommens des Landes Schleswig-Holstein nutzen wir eine Echtzeitdatenbank der nominalen Steuereinnahmen. Als Evaluationskriterium dient uns der verfahrensspezifische Revisionsbedarf der Steuertrendschätzung wie sie durch einen erweiterten Informationsstand der Finanzplanung im Zeitverlauf entsteht.

Keywords: Finanz- und Haushaltsplanung, quantitative Budgetsicherheit, Steueraufkommensprognose, Konjunkturbereinigungsverfahren, Schuldenbremse, kommunaler Finanzausgleich.

JEL classification: C22, C52, C53, H68, H72, H83

5.1 Einleitung

Gegenstand dieses Gutachtens ist die Entwicklung und Evaluation einer geeigneten Methodik zur Ermittlung des Trendsteuerpfades im Sinne der langfristig zu erwartenden Entwicklung des Steueraufkommens des Landes Schleswig-Holstein unter Berücksichtigung des geltenden Landes- und übergeordneten Bundesrechts. Die Prognose der langfristigen Steuerentwicklung ist die entscheidende Größe bei der Ermittlung und Fortschreibung der Einnahmeseite des Landeshaushalts im Zuge der mittelfristigen Haushaltsplanung. Ab 2020 haben sich die Länder dabei im Rahmen der Schuldenbremse verpflichtet, ausgabenseitig eine strukturelle, das heißt konjunkturbereinigte Neuverschuldung von Null zu erreichen. Zudem findet über die Koppelung der Landesausgaben an den langfristigen Einnahmetrend eine Glättung der Ausgaben über die Zeit statt, die dazu beiträgt, unerwünschte, konjunkturbedingte Finanzierungslücken zu vermeiden.

An ein geeignetes Verfahren zur Extraktion und Extrapolation des Trendsteuerverlaufs sind verschiedene Anforderungen zu stellen. Zunächst kommen nur solche Verfahren in Frage, welche die gesetzlich kodifizierten Rahmenbedingungen erfüllen und sich darüber hinaus durch größtmögliche Objektivität, Transparenz und Wirtschaftlichkeit auszeichnen. Bei der Evaluation des Extrapolationsverfahrens stellt sich grundsätzlich das Problem, dass Trend– und Konjunkturkomponente jeweils nicht beobachtbar sind und aus der vorliegenden Realisation der Steuerzeitreihe geschätzt werden müssen. Es kann also auch *ex post* die Prognosegüte eines Modells nicht ohne Weiteres durch den Vergleich von prognostizierten und realisierten Größen beurteilt werden. Bei der Evaluation konzentrieren wir uns daher in diesem Gutachten auf das Kriterium der Stabilität des Trendsteuerpfades bezüglich der regelmäßigen Aktualisierungen des Datenstandes. Eine hohe Trendstabilität erhöht grundsätzlich auch die Planungssicherheit, während erhebliche Trendrevisionen als Folge eines erweiterten Informationsstandes mit Anpassungskosten verbunden sind.

Dieses Gutachten ist wie folgt strukturiert. Kapitel 5.2 erläutert die gesetzlichen Anforderungen an das Verfahren zur Trendsteuerermittlung. Kapitel 5.3 skizziert die verwendete Datengrundlage sowie die Berücksichtigung historischer Steuerrechtsänderungen. Kapitel 5.4 diskutiert alternative Verfahren zur Ermittlung der Trendsteuereinnahmen unter Berücksichtigung der Auftrags- und Gesetzesgrundlage. In Kapitel 5.5 wird die Vorgehensweise der Projektion der Steuereinnahmen beschrieben. Kapitel 5.6 ist der Evaluation der alternativen Verfahren bezüglich des erwarteten Revisionsbedarfs gewidmet und Kapitel 5.7 kommt zu einer abschließenden Zusammenfassung und Empfehlung.

5.2 Gesetzliche Rahmenbedingungen

Die diesem Gutachten zugrunde liegende Gesetzeslage für die Ermittlung der konjunkturbereinigten Steuereinnahmen umfasst Artikel 109 und 115 des Grundgesetzes (GG) der Bunderepublik Deutschland in der Fassung vom 11.07.2012 sowie nachgeordnet die Artikel 53 und 59a (Übergangsvorschrift) der Verfassung des Landes Schleswig-Holstein (LV) in der Fassung vom 22.07.2010 und das Ausführungsgesetz (AG) zu Artikel 53 der Verfassung des Landes

Schleswig-Holstein (Entwurf vom 07.02.2012).
Sowohl das GG als auch die LV verlangen dabei eine symmetrische Berücksichtigung der Auswirkungen einer von der Normallage abweichenden konjunkturellen Entwicklung bei der Haushaltsaufstellung (vgl. GG Artikel 109 Satz 3; LV 53 Satz 2 und 3). Näheres zum Konjunkturbereinigungsverfahren regelt das entsprechende Ausführungsgesetz zu Artikel 53 der LV. § 6 Absatz 3 definiert dabei die Steuereinnahmen im Sinne des Gesetzes als die Einnahmen aus Steuern, aus dem Länderfinanzausgleich, aus Bundesergänzungszuweisungen und aus der Kfz-Steuerkompensation abzüglich der Ausgaben für den Länderfinanzausgleich. Absatz 4 definiert die Beziehung der Trendsteuerniveaus zweier aufeinander folgender Haushaltsjahre über die Wachstumsrate der Trendsteuereinnahmen. Absatz 6 des AG fordert, dass die Wachstumsrate und damit letztlich auch die Trendsteuereinnahmen so zu bestimmen sind, dass mittelfristig der kumulierte Saldo der Konjunkturkomponenten gegen Null tendiert (*Symmetriekriterium*). Diese Konjunkturkomponente ist als Differenz zwischen den Steuereinnahmen gemäß § 6 Absatz 3 und dem gemäß den Absätzen 3 bis 6 zu bestimmenden langfristigen Steuereinnahmen (Trendsteuereinnahmen) zu ermitteln. Zudem regelt Absatz 6, dass bei der Bestimmung der Wachstumsrate ein hinreichend langer Zeitraum zugrunde zu legen ist, der die Zeitspanne von zwei aufeinander folgenden Konjunkturzyklen nicht unterschreiten sollte. Hierdurch soll insbesondere dem strukturellen, langfristigen Aspekt der Neuverschuldung über den Konjunkturzyklus hinweg Rechnung getragen werden. Neben dem von GG und LV geforderten Symmetriekriterium wird durch § 6 Absatz 2 des AG die Ermittlung einer entsprechenden Konjunkturkomponente, welche im Haushaltsplan darzustellen ist, gefordert (vgl. AG § 6 Absatz 7).

Ziel dieses Gutachtens wird es daher ebenfalls sein, die entsprechende Konjunkturkomponente für die kurze, mittlere und lange Frist über den Finanzplanungszeitraum hinaus für 10 Jahre in die Zukunft darzustellen. Dies geschieht unter Berücksichtigung der Mittelfristprojektionen des Arbeitskreises Steuerschätzungen (AKS), da diese eine feste Größe für die Finanzplanung darstellen. Eine zentrale Annahme des AKS ist dabei, dass die Wirtschaft innerhalb von zwei Jahren auf den Potentialwachstumspfad zurückkehrt.[1]

5.3 Datengrundlage und Steuerrechtsänderungen

Als Datengrundlage dienen die vom Finanzministerium des Landes Schleswig-Holstein zur Verfügung gestellten nominalen Daten über die Steuereinnahmen des Landes nach AG, §-6, Absatz 3 sowie der folgenden Unteraggregate: Summe der Einnahmen des Landes aus Steuern (Gemeinschaftssteuer, Landessteuer), Einnahmen aus dem Länderfinanzausgleich und Einnahmen aus den Bundesergänzungszuweisungen (inkl. Kfz-Steuerkompensationen). Die Steuereinnahmen stellen dabei über den Zeitraum von 1990 bis 2011 mit einem durchschnittlichen Anteil von circa 94 vH den größten Einnahmeblock des Landes dar.[2] Dementsprechend entfallen auf die Zuweisungen anderer staatlicher Ebenen lediglich 6 vH, wobei der Sachverständigenrat zur Begutachtung der gesamtwirtschaftlichen Entwicklung (SVR) für diese Ein-

[1] vgl. z.B., “Schleswig-Holsteinischer Landtag Umdruck 18/1859”, vom 12.11.2013, S.2
[2] Eigene Berechnungen.

nahmen der Länder keine Konjunkturabhängigkeit feststellt. Basierend hierauf stellt der SVR zutreffend fest, dass Unterschiede zwischen der Betrachtung der gesamten Einnahmen und einer Einzelbetrachtung der Komponenten mit anschließender Aggregation nicht wesentlich ins Gewicht fallen (vgl. SVR 2007, "Staatsverschuldung wirksam begrenzen.", S.125). Eine Konjunkturbereinigung der gesamten Einnahmen ist damit für Schleswig-Holstein sowohl aus ökonomischer als auch aus wirtschaftlicher bzw. administrativer Sicht zu bevorzugen. Die betrachteten Datenreihen umfassen dabei jährliche Ist-Daten für den Zeitraum 1981 bis 2012 sowie Projektionen (Soll-Daten) des Arbeitskreises Steuerschätzungen (AKS) für den mittelfristigen Finanzplanungszeitraum bis 2018. Der SVR identifiziert für diesen Zeitraum zwei abgeschlossene Konjunkturzyklen von 1982 bis 1993 und 1993 bis 2003, sodass § 6, Absatz 6 des AG bezüglich der zugrunde zu legenden Zeitspanne für die Ermittlung des Trendsteuerpfades genüge getan ist (vgl. SVR, Jahresgutachten 03/04, S.418, Ziffer 575).

Darüber hinaus hat das Ministerium Echtzeitdatenstände zur Verfügung gestellt, welche im Rahmen der Evaluation der vorgeschlagenen Methodik verwendet werden. Diese Echtzeitdatenstände versetzen uns in die Lage, auf Basis der historischen Ist- und Soll-Datenstände, wie sie für die Haushaltsplanungen zwischen 2000 und 2012 genutzt wurden, jeweils die resultierenden langfristigen Steuereinnahmen zu schätzen und mit den nach heutigem (ex post) Informationsstand geschätzten langfristigen Steuereinnahmen zu vergleichen. Die Relevanz dieses Vergleichs ergibt sich daraus, dass die Soll-Daten über die zukünftige Entwicklung der Steuereinnahmen regelmäßig (zweimal im Jahr) durch den Arbeitskreis Steuerschätzungen revidiert bzw. durch Ist-Daten ersetzt werden. Da die Steuereinnahmen Basis für die Ermittlung des Trendsteuerpfades sind, entsteht auch für die langfristige Steuerentwicklung Revisionsbedarf.

Die Steuereinnahmen des Landes sind in der Vergangenheit wiederkehrend strukturellen Anpassungen durch Steuerrechtsänderungen unterlegen. Diese Änderungen sind bei der Bestimmung des Trendsteuerpfades und bei der Projektion der Steuereinnahmen über den Projektionszeitraum des Arbeitskreises Steuerschätzungen hinaus zu berücksichtigen. Die vom Finanzministerium Schleswig-Holstein zur Verfügung gestellten Daten sind dabei bereits um Steuerrechtsänderungen korrigiert, insbesondere um die Einführung der Kfz-Steuerkompensation durch den Bund im Mai 2009. Außerdem wurden die Einnahmen des Landes um die Sondereffekte aus den ab 2011 gewährten Konsolidierungshilfen bereinigt.

5.4 Methodik der Trendsteuerermittelung

Zur Ermittlung des Trendsteuerpfades stehen prinzipiell eine Vielzahl ökonometrischer Verfahren zur Verfügung, die mangels einer eigenständigen Literatur zur Trendsteuerschätzung aus dem Bereich der Konjunkturanalyse entliehen und dort erprobt sind. Diese können dabei zum einen in Hinblick auf die zur Trendschätzung verwendete Informationsgrundlage in univariate und multivariate Verfahren klassifiziert werden. Zum anderen lassen sich rein statistische von solchen Vorgehensweisen unterscheiden, die aus einem ökonomischen Modell abgeleitet werden, wobei es sich bei letzteren in der Regel gleichzeitig um multivariate Verfahren handelt (vgl. z.B. SVR, JG 03/04). Vor dem Hintergrund des Anforderungskatalogs an das Konjunkturbereinigungsverfahren empfehlen sich univariate statistische Verfahren. Diese nutzen im Gegensatz zu multivariaten Verfahren nur die historische Information der Steuerzeitreihe selbst und stellen daher die transparentere, objektivere und letztlich auch wirtschaftlichere Wahl dar.[3] Insbesondere der Hodrick-Prescott Filter (Hodrick und Prescott 1997) erfüllt dabei außerdem alle gesetzlichen Rahmenbedingungen, wie im Folgenden erläutert werden soll.

5.4.1 Der Hodrick–Prescott (HP) Filter

Der grundlegende Ansatz statistischer Filterverfahren zur Trendermittlung ist die Zerlegung einer in den Perioden (hier: Jahren) $t = 1, 2, \ldots, T$ beobachteten Zeitreihe y_t (hier: die Steuereinnahmen[4]) in eine „glatte" Trendkomponente y_t^* und eine zyklische Konjunkturkomponente k_t, sodass

$$y_t = y_t^* + k_t, \tag{5.1}$$

wie in Anlehnung an § 6 Absatz 2 des AG gefordert. Dabei repräsentiert y_t^* in Gleichung (5.1) den Trendsteuerpfad, der die längerfristige Entwicklung der Steuereinnahmen möglichst gut widerspiegeln soll. Daraus ergibt sich als erste Forderung an die Trendfunktion, dass sie sich durch eine insgesamt gute Anpassung an die beobachtete Steuerzeitreihe auszeichnen soll. Um eine endogene Anpassung der Trendwachstumsrate zu ermöglichen, soll y_t^* nicht parametrisch restringiert werden (wie es etwa bei Unterstellung einer linearen Trendfunktion der Fall wäre). Es wird aber (zweitens) gefordert, dass der Trendverlauf „glatt" sein soll. Als Maß für die Glattheit der Trendfunktion verwendet der HP Filter die Veränderungen in der Steigung der Trendfunktion ($\Delta y_{t+1}^* = y_{t+1}^* - y_t^*$) zwischen zwei aufeinanderfolgenden Perioden, d.h. die zweiten Differenzen

$$\Delta^2 y_{t+1}^* = \Delta y_{t+1}^* - \Delta y_t^* = (y_{t+1}^* - y_t^*) - (y_t^* - y_{t-1}^*). \tag{5.2}$$

Misst man ferner die Distanz zwischen der Trendfunktion und der Steuerzeitreihe durch die Summe der quadratischen Abweichungen (Kriterium der kleinsten Quadrate), so führt die Abwägung zwischen den beiden oben erhobenen Forderungen an den Trendverlauf auf das Minimierungsproblem

$$\min_{y_1^*,\ldots,y_T^*} \sum_{t=1}^{T} (y_t - y_t^*)^2 + \lambda \sum_{t=2}^{T-1} [(y_{t+1}^* - y_t^*) - (y_t^* - y_{t-1}^*)]^2, \tag{5.3}$$

[3] Kydland and Prescott (1990) nennen als Grund für die Wahl des Hodrick-Prescott Filters u.a., dass „[t]he scheme should be well defined, judgment free, and cheaply reproducible."

[4] Die Trendkomponente wird oft unter Verwendung logarithmierter Zeitreihen extrahiert. Obgleich damit gewisse Vorzüge einhergehen, liegen den Berechnungen in diesem Gutachten die untransformierten Steuereinnahmen zugrunde, da, wie in Kapitel 5.2 dargelegt, der Entwurf des Ausführungsgesetzes zu Artikel 53 der LV eine additive Zerlegung dieser Zeitreihe in eine Trend– und eine Konjunkturkomponente fordert. Auch der Symmetrieanforderung wird auf diese Weise per Konstruktion nachgekommen. Die Unterschiede zwischen den Ergebnissen beider Vorgehensweisen sind darüber hinaus aber undramatisch. So liegen die ermittelten Abweichungen im Trendsteuerverlauf durchgängig unterhalb von 2%, und mit Ausnahme weniger Trendwerte am *linken* (also weit zurückliegenden) Rand der Reihe sogar unterhalb von 1%.

wobei der „Glättungsparameter” λ der einzige festzulegende Parameter ist. Der Parameter λ “bestraft” dabei die Veränderung der Steigung des Trendverlaufs $\Delta y_t^* = y_t^* - y_{t-1}^*$ und legt somit letztlich das Ausmaß der Glättung bei der Trendschätzung fest. Je größer λ gewählt wird, desto glatter stellt sich der Trendverlauf dar: Für sehr großes λ („$\lambda \to \infty$”) erhält man einen linearen Trendverlauf und dementsprechend keine Steigungsvariation. Wird $\lambda = 0$ gesetzt, so entfällt der Strafterm in (2) und der geschätzte Trend entspricht genau den Steuereinnahmen ($y_t^* = y_t$ für alle t). Es besteht ein weitgehender Konsenz in der Literatur hinsichtlich des ungefähren Wertes für λ, wobei für Jahresdaten typischerweise ein $\lambda \approx 100$ gewählt wird (vgl. SVR 2007, Staatsverschuldung wirksam begrenzen). Darüber hinaus wird durch die Wahl eines hinreichend kleinen Wertes für λ im Gegensatz zu deterministischen Trendverläufen, wie zum Beispiel im Rahmen von Spline-Regressionen (vgl. SVR JG 03/04), eine endogene Trendkorrektur möglich, sodass der HP Filter aus Gründen der Objektivität vorzuziehen ist.

Der HP Filter hat für die vorliegende Problemstellung weitere vorteilhafte Eigenschaften. Durch das bei der Minimierung der Funktion (5.3) zugrunde gelegte Kriterium der kleinsten Quadrate ist die Symmetrie-Eigenschaft gemäß § 6 Absatz 1 und 2 des AG stets per Konstruktion erfüllt. Dementsprechend ist ein gedachtes Kontrollkonto nach aktueller Datenlage stets ausgeglichen, sodass die Summe der Konjunkturkomponenten k_t gleich Null ist. Legt man nun für die Trendschätzung exakt den Zeitraum eines Konjunkturzyklus zugrunde, erhält man auf Basis des HP Filters eine strukturelle Neuverschuldung von Null. Da Konjunkturzyklen im allgemeinen nur ex post bestimmt werden können (vgl. z.B. SVR JG 03/04), erhält man jedoch bei hinreichend langem Schätzzeitraum, wie in § 6 Absatz 6 des AG gefordert, die beste ex ante mögliche Annäherung. Aufgrund dieser Eigenschaften wird der HP Filter ebenfalls vom Sachverständigenrat zur Begutachtung der gesamtwirtschaftlichen Entwicklung im Rahmen von Konjunkturbereinigungsverfahren verwendet:

“Der Sachverständigenrat verwendet den HP Filter [...] bei der Ermittlung des konjunkturbereinigten staatlichen Defizits. Für den HP Filter sprechen in diesem Zusammenhang vor allem dessen Einfachheit und das Kriterium der Transparenz, da der HP Filter in der empirischen Anwendung vergleichsweise wenig Spielraum für Willkür lässt.”
(SVR 2007, “Staatsverschuldung wirksam begrenzen”, S.136)

5.4.2 Modifizierter HP (MHP) Filter

Wie bereits dargelegt, ist die Literatur zur Ermittlung der langfristigen Steuereinnahmen im Rahmen der Schuldenbremse bisher nicht sehr weit fortgeschritten. Eine Ausnahme macht hier die schweizerische Eidgenössische Finanzverwaltung (EFV), welche schon seit dem Jahr 2003 die Schuldenbremse für die Schweiz und ihre Kantone und Gemeinden implementiert hat und ihre Erfahrungen veröffentlicht. Die EFV hat im Zuge der Implementation zunächst ebenfalls die oben beschriebene Version des HP Filters angewendet, um ihn dann aber durch eine modifizierte Version (MHP Filter) zu ersetzen (vgl. EVF 2004, Eine Neubewertung der Schuldenbremse). Auf Basis der vom Finanzministerium Schleswig-Holstein zur Verfügung

gestellten Echtzeitdatenstände lässt sich rückwirkend die Vorteilhaftigkeit des MHP Filters im Vergleich zur nicht modifizierten Variante anhand des in Kapitel 5.6 beschriebenen Vorgehens für das Land Schleswig-Holstein evaluieren. Daher soll zunächst der modifizierte HP Filter kurz begründet und skizziert werden.
Die Begründung der Modifikation ergibt sich aus der Tatsache, dass im Minimierungsproblem (5.3) die ersten beiden sowie die letzten beiden Beobachtungen nur einmal respektive zweimal im Strafterm berücksichtigt werden, während alle übrigen Beobachtungen dreimal auftauchen. Dies kann beim nicht modifizierten HP Filter zur Folge haben, dass der geschätzte Trend tendenziell relativ stark auf Veränderungen am aktuellen Datenrand reagiert, beispielsweise auf Revisionen der geschätzten Steuereinnahmen im Zuge der Haushaltsplanung. Als Lösung wird daher in der oben angegebenen Referenz vorgeschlagen, das Gewicht der ersten und letzten beiden Beobachtungen auch im ersten Teil der Funktion (5.3) proportional zu verringern, also die Minimierungsaufgabe (5.3) durch

$$\min_{y_1^*,\ldots,y_T^*} \sum_{t=1}^{T} w_t (y_t - y_t^*)^2 + \lambda \sum_{t=2}^{T-1} [(y_{t+1}^* - y_t^*) - (y_t^* - y_{t-1}^*)]^2, \tag{5.4}$$

zu ersetzen, wobei der Unterschied lediglich in der neu hinzugekommenen Gewichtsfunktion w_t besteht, mit

$$w_t = \begin{cases} \frac{1}{3} & \text{für } t = 1 \text{ und } t = T \\ \frac{2}{3} & \text{für } t = 2 \text{ und } t = T-1 \\ 1 & \text{für alle anderen Zeitpunkte.} \end{cases}$$

Der benannte Gewichtungseffekt kann bei hinreichend geringem Projektionsfehler allerdings vernachlässigbar sein. Der SVR sieht im Rahmen seiner Evaluation des Verfahrens für die Bundesrepublik Deutschland keinen Vorteil in der Verwendung der modifizierten Variante des HP Filters (vgl. SVR 2007, Staatsverschuldung wirksam begrenzen). Die Vorteilhaftigkeit der einen oder anderen Variante ist in jedem Fall auf Länderebene gesondert zu prüfen.

5.5 Fortschreibung der Steuereinnahmen

Unter Anwendung der in diesem Gutachten vorgeschlagenen Methodik soll der Trendsteuerpfad über das laufende Haushaltsjahr hinaus für 10 Jahre in die Zukunft ermittelt werden. Dabei gehen wir in zwei Schritten vor. Zunächst schreiben wir die Zeitreihe der *Steuereinnahmen* in die Zukunft fort, um aus dieser fortgeschriebenen Zeitreihe anschließend unter Verwendung des in Kapitel 5.4 beschriebenen HP Filters die Trend– und Konjunkturkomponenten zu extrahieren.

Dieses zweistufige Vorgehen hat den Vorteil, dass durch die Fortschreibung der Steuereinnahmen mit anschließender Trendextraktion auch die Ausweisung (bzw. Projektion) der Konjunkturkomponente über den gesamten Zeitraum für 10 Jahre in die Zukunft ermöglicht wird.

Der Arbeitskreis Steuerschätzungen (AKS) stellt Projektionen für den mittelfristigen Finanzplanungszeitraum, das heißt für 5 Jahre in die Zukunft, zur Verfügung. Es ergibt sich daher im Rahmen dieses Gutachtens ein über die Projektionen des AKS hinausgehender Fortschreibungsbedarf. Zu diesem Zweck greifen wir auf die Modellklasse der univariaten ARIMA Modelle[5] zurück (Box et al., 2008). Mit diesen Standardmodellen der Zeitreihenökonometrie liegen auch auf dem Anwendungsfeld der Projektion von Steueraufkommensgrößen bereits umfangreiche Erfahrungen vor (vgl. z.B. Berberich, 2012). Zudem verwenden diese Modelle analog zu den in Kapitel 5.4 dargelegten Filterverfahren wiederum nur die historische Information aus der Steuerzeitreihe, wodurch die Objektivität und die Nachvollziehbarkeit der Ergebnisse (Transparenz) gewährleistet werden.

Zur Spezifikation des ARIMA-Modells wurden zunächst die Dateneigenschaften der Steuerzeitreihe des Landes Schleswig-Holstein ermittelt. Ein Einheitswurzel-Test (ADF-Test) ergibt, dass die Steuereinnahmen integriert vom Grade eins sind. Die anschließende Modellspezifikation für die ersten Differenzen der logarithmierten Steuereinnahmen führt auf einen autoregressiven Prozess zweiter Ordnung auf Basis der zur Verfügung stehenden Datengrundlage von 1981 bis 2018 (einschließlich der Projektionen des AKS). Die abschließende Modelldiagnose nach dem Box-Jenkins Verfahren zeigt keine Evidenz für einen informativen Residualprozess, sodass die oben genannte Spezifikation dazu geeignet scheint, die Information der Steuerzeitreihe zufriedenstellend abzubilden. Das autoregressive Modell für die erste Log-Differenz der Steuereinnahmen Δy_t im Beobachtungszeitraum von 1984 bis 2018[6] ergibt sich damit als

$$\Delta y_t = \beta_0 + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + \epsilon_t \tag{5.5}$$

wobei β_0, β_1 und β_2 die entsprechenden (zu schätzenden) Parameter des Modells und ϵ_t ein Störterm, der weißes Rauschen darstellt. Unter Verwendung des geschätzten Modells wurden die entsprechenden Projektionen der ersten Log-Differenz der Steuereinnahmen berechnet und diese dann im Niveau vom aktuellen Rand des Soll-Datenstandes aus fortgeschrieben. Die Ergebnisse der für den Zeitraum 1981 bis 2023 finden sich in Tabelle 2 respektive Abbildung 1 (Anhang).

Die hier ermittelte Modellspezifikation sowie die Schätzung der Parameter wurde auf Basis der aktuellen Datengrundlage ermittelt. Daher ist darauf hinzuweisen, dass sowohl die Spezifikation als auch die Parameterschätzung bei Aufnahme neuer bzw. Revision alter Datenpunkte regelmäßig zu überprüfen sind.

5.6 Evaluation der Trendstabilität

Wie in Kapitel 5.1 erläutert, soll als Kriterium bei der Evaluation der alternativen Filtervarianten die Trendstabilität im Hinblick auf Soll-Datenrevisionen und Ersetzungen von Soll- durch Ist-Datenstände herangezogen werden. Dafür wurden sowohl für den HP (Kap. 5.4.1) als auch den MHP (Kap. 5.4.2) Filter Trendschätzungen basierend auf den jeweiligen Ist- und Solldatenständen, wie sie für die Haushaltsplanungen der Jahre 2000 bis 2012 verwendet wurden, mit der aus dem jeweiligen Verfahren resultierenden ex post Trendschätzung basierend

[5] Dies ist das gängige Kürzel für **A**uto**R**egressive **I**ntegrierte **M**oving **A**verage Modelle.

[6] Der Beobachtungszeitraum beginnt hier entsprechend 1984, da die Jahre 1981 bis 1983 für die Bildung der ersten Differenz und für die verzögerten erklärenden Variablen genutzt wurden.

auf dem zum heutigen Zeitpunkt bekannten Informationsstand verglichen.[7]
Zur Durchführung des Vergleichs wurde die Wurzel der mittleren quadratischen Abweichung (RMSE[8]) zwischen der jeweiligen ex ante $y^*_{i,ea}$ und der entsprechenden ex post Trendschätzung $y^*_{i,ep}$ über die für die Haushaltsplanung relevanten Perioden $i = 1, ..., N$ für beide Verfahren ermittelt,[9] d.h.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y^*_{i,ep} - y^*_{i,ea})^2}. \tag{5.6}$$

Eine kleinere Abweichung geht dabei mit einem stabileren Trendverlauf einher. Die Vorteilhaftigkeit wurde dabei sowohl für den kurzen, das laufende und das kommende Haushaltsjahr umfassenden, als auch für den mittelfristigen, fünf Jahre in die Zukunft reichenden Finanzplanungszeitraum getrennt evaluiert. Für die Evaluation der kurzen Frist wurden dabei sowohl die Datenstände der Mai– als auch der November–Projektionen des AKS verwendet. Dagegen wurden für die mittlere Frist nur die Mai–Projektionen herangezogen, da die November–Projektionen erst ab 2011 den gesamten Mittelfristzeitraum abdecken.[10] Die Ergebnisse des Vergleichs finden sich in Tabelle 1.

Tabelle 1

Evaluationsergebnisse: Wurzel der mittleren quadratischen Abweichung
des Trendsteuerpfades nach dem HP Filter sowie nach dem modifizierten (MHP) Filter
für die kurze und mittlere Frist der Finanzplanung.

	HP Filter	**MHP Filter**
kurze Frist	$\mathbf{268,868}$	$281,904$
mittlere Frist	$\mathbf{403,736}$	$424,083$

Quelle: Eigene Berechnungen.

Wie aus einem Spaltenvergleich in Tabelle 1 ersichtlich wird, weißt das HP Filterverfahren sowohl in der kurzen als auch in der mittleren Frist über den Evaluationszeitraum von 2000 bis 2012 die geringere (mittlere) quadratische Abweichung auf. Damit ist dieses Verfahren in Hinblick auf die Stabilität und damit letztlich auf die Planungssicherheit des Haushaltes zu bevorzugen.

Die Ergebnisse der ARIMA Projektionen der Steuereinnahmen sowie der Trendschätzung nach dem HP Filterverfahren sind in der Tabelle 2 und 3 dargestellt (Appendix 2).

[7] Für die ex post Trendschätzung wurde dabei der Ist-Datenzeitraum von 1981 bis 2012 sowie die Projektionen des AKS bis 2018 verwendet.
[8] **R**oot **M**ean **S**quared **E**rror.
[9] Die quadratische Abweichung wurde gewählt, um sowohl positiven als auch negativen Abweichungen gleichermaßen Rechnung zu tragen.
[10] Vor dem Jahr 2011 wurden im November nur Projektionen für das laufende und folgende Haushaltsjahr durch den AKS bereitgestellt.

5.7 Zusammenfassende Empfehlung

Dieses Gutachten hatte die Entwicklung und Evaluation einer Methode zur Ermittlung und Projektion des Trendsteuerpfades für das Land Schleswig-Holstein zum Gegenstand. Dabei galt es zunächst, vor dem Hintergrund der gesetzlichen Rahmenbedingungen und der Ausschreibungskriterien wie Objektivität, Transparenz und Wirtschaftlichkeit geeignete ökonometrische Vorgehensweisen zur Trendermittlung zu identifizieren. Es wurde argumentiert, dass im Hinblick auf die angeführten Anforderungen die Konzentration auf die Klasse univariater statistischer Filterverfahren angeraten werden kann. Insbesondere das in der ökonometrischen Literatur als Hodrick–Prescott (HP) Filter bekannt gewordene Konjunkturbereinigungverfahren wurde als besonders geeignet ausgemacht, da es insbesondere auch alle gesetzlichen Anforderungen erfüllt, die an die Trendermittlung gestellt werden.

Da der Arbeitskreis Steuerschätzungen Mittelfristprojektionen der Steuereinnahmen für 5 Jahre in die Zukunft zur Verfügung stellt, der Trendsteuerpfad als Grundlage für die Finanzplanung jedoch für 10 Jahre in die Zukunft zu ermitteln ist, ergab sich im Rahmen dieses Gutachtens ein über die Projektionen des Arbeitskreises hinausgehender Fortschreibungsbedarf. Prinzipiell sind hier zwei Vorgehensweisen möglich. Zum einen kann der Trendsteuerpfad auf Basis der Projektionen des Arbeitskreises bis in die mittlere Frist geschätzt und anschließend weiter fortgeschrieben werden. Zum anderen kann auch die Reihe der Steuereinnahmen selbst projeziert werden, um dann als Grundlage für die Ermittlung des Trendsteuerpfades zu dienen. In diesem Gutachten wurde die zweite Möglichkeit vorgezogen, da diese auch die Ausweisung einer Konjunkturkomponente über den gesamten Zeitraum für 10 Jahre in die Zukunft ermöglicht. Zum Zweck der Fortschreibung wurden zeitreihenökonometrische Standardmodelle verwendet, für die insbesondere auch aus dem Bereich der Steuerprojektion umfangreiche Erfahrungen dokumentiert sind.

Zur Evaluation wurden zwei verschiedene Versionen des HP Filters, die in Kapitel 4 jeweils näher beschrieben wurden, im Hinblick auf das Kriterium "Planungssicherheit" miteinander verglichen. Da der Trendsteuerpfad als unbeobachtbare Größe aus dem jeweils aktuellen Ist- und Soll-Datenstand der Steuereinnahmen geschätzt werden muss, unterliegt er im Zeitverlauf regelmäßigen Korrekturen im Zuge der Ersetzung von Soll- durch Ist-Datenpunkte sowie der halbjährlichen Aktualisierung der Steuerschätzungen durch den ensprechenden Arbeitskreis. Ein Minimum an Korrekturbedarf geht dabei mit einem Maximum an Planungssicherheit einher. Wie in Kapitel 6 dargelegt, stellte sich für die Ermittlung des Trendsteuerpfades der Steuereinnahmen des Landes Schleswig-Holstein die Standardvariante des Filters gegenüber der modifizierten Version der schweizerischen Eidgenössischen Finanzverwaltung als vorteilhaft heraus.

Diesem Gutachten ist eine Stellungnahme zur Ausgestaltung des kommunalen Finanzausgleichs angefügt. Ebenfalls basierend auf dem Argument der Planungssicherheit der Zuweisungsempfänger empfiehlt es sich, nicht nur die Ausgaben des Landes, sondern auch die Zuweisungen des Landes an die Gemeinden, Kreise und Ämter an den Trendsteuerpfad zu koppeln statt wie bisher als Berechnungsgrundlage die nicht konjunkturbereinigten Einnahmen des Landes zugrunde zu legen.

Gemeinsam mit diesem Gutachten erfolgt die Bereitstellung einer Excel-Lösung zur hausinternen Ermittlung des jeweils aktuellen Trendsteuerpfades durch das Finanzministerium Schleswig-Holstein. Diese Lösung ermöglicht dem Finanzministerium die eigenständige Aktualisierung der Trendschätzungen nach den jeweils neuesten Informationsständen, insbesondere auch die hierzu notwendige Fortschreibung der Steuereinnahmen bis 10 Jahre in die Zukunft. Dabei ist darauf hinzuweisen, dass das der Fortschreibung zugrunde gelegte Modell sowie die zugehörigen Schätzungen der Modellparameter einer regelmäßigen Prüfung und ggf. Aktualisierung unterzogen werden sollten.

5.8 Bibliographie

Berberich, U. (2012) “Steuerschätzung und Analyse der Prognosegüte für die Bundesrepublik Deutschland” Dissertation, Universität Hohenheim.

Box, Jenkins und Reinsel (2008) *“Time Series Analysis: Forecasting and Control"*. 4te Edition. Wiley, New Jersey.

Bruchez (2003), “A Modification of the HP Filter Aiming at Reducing the End-Point Bias", Eidg. Finanzverwaltung, Working Paper.

Colombier *et al.* (2004), “Eine Neubewertung der Schuldenbremse", Eidg. Finanzverwaltung.

Gesetz über den Finanzausgleich in Schleswig-Holstein (2011) in der Fassung der Bekanntmachung vom 07. M¨arz 2011.

Grundgesetz für die Bundesrepublik Deutschland (2012), vom 11.07.2012.

Kydland und Prescott (1990), “Business Cycles: Real Facts and a Monetary Myth", Federal Reserve Bank of Minneapolis *Quarterly Journal*, 3-18.

Hodrick und Prescott (1997), “Postwar US Business Cycles: An Empirical Investigation", Journal of Money, Credit and Banking, 29, 1-16.

Landesregierung Schleswig-Holstein (2012), Entwurf eines Gesetzes zur Ausführung von Artikel 53 der Verfassung des Landes Schleswig-Holstein, Drucksache 17/2248 vom 02.07.2012.

Sachverständigenrat zur Begutachtung der gesamtwirtschaftlichen Entwicklung (2003), “Jahresgutachten 2003/04: Staatsfinanzen konsolidieren - Steuersystem reformieren”.

Sachverständigenrat zur Begutachtung der gesamtwirtschaftlichen Entwicklung (2007), “Staatsverschuldung wirksam begrenzen.”.

Schleswig-Holsteinischer Landtag, Umdruck 18/1859 vom 12.11.2013, “Ergebnis der 143. Sitzung des Arbeitskreises Steuerschätzungen vom 5. bis 7. November 2013 in Bremerhaven.”.

Verfassung des Landes Schleswig-Holstein (2008), vom 13.05.2008.

5.9 Appendix 1: Stellungnahme zur Ausgestaltung des kommunalen Finanzausgleichs

Im Finanzausgleichsgesetz (FAG)[11] ist festgelegt, dass das Land den Gemeinden, Kreisen und Ämtern zur Deckung ihres allgemeinen Finanzbedarfs allgemeine Finanz- und Zweckzuweisungen gewährt (vgl. FAG § 2 Absatz 1). Die Höhe der gesetzlich festgeschriebenen Finanzausgleichs ist dabei zeitvariabel gestaltet. Diese Finanzaußgleichsmasse nach § 5 Absatz 1 wird zurzeit als Verbundsatz in Höhe von 17,74 vH aus den nicht konjunkturbereinigten Einnahmen des Landes aus Steuern, der Kfz-Steuerkompensation, den Ergänzungszuweisungen des Bundes sowie den Einnahmen aus dem Länderfinanzausgleich berechnet. Somit ist die Zusammensetzung der Berechnungsgrundlage für den kommunalen Finanzausgleich letztlich identisch mit den in diesem Gutachten betrachteten Steuereinnahmen des Landes nach dem Ausführungsgesetz zu Artikel 53 der LV § 6 Absatz 3. Die Finanzausgleichsmasse wird dabei für jedes Haushaltsjahr nach den Ansätzen im Landeshaushaltplan festgesetzt (vgl. § 5 Absatz 2 FAG). Da diese Ansätze zur zukünftigen Einnahmeentwicklung des Landes, wie im Laufe dieses Gutachtens bereits erläutert, nicht konjunkturbereinigte Größen darstellen, ist im Rahmen des kommunalen Finanzausgleichs eine regelmäßige Verrechnung von Mehr- bzw. Minderzahlungen notwendig. Neben den administrativen Kosten der Verrechnung führt diese Vorgehensweise tendenziell zu einnahmeseitiger Planungsunsicherheit für die Gemeinden, Kreise und Ämter, da die Finanzausgleichsmasse somit konjunkturellen Schwankungen unterliegt. Aus ökonomischer Sicht ist daher zu empfehlen, den Verbundsatz alternativ auf die in diesem Gutachten ermittelten Trendsteuereinnahmen anzulegen, sodass auch die Finanzausgleichsmasse konjunkturbereinigt ist und damit letztlich auch die Einnahmen der Gemeinden, Kreise und Ämter aus Finanz- und Zweckzuweisungen über die Zeit geglättet werden. Zudem würden dann die administrativen Kosten der Verrechnung von konjunkturbedingten Mehr- und Minderzuweisungen entfallen.

[11] Gesetz über den Finanzausgleich in Schleswig-Holstein in der Fassung der Bekanntmachung vom 07. März 2011.

5.10 Appendix 2: Tabellen und Abbildungen

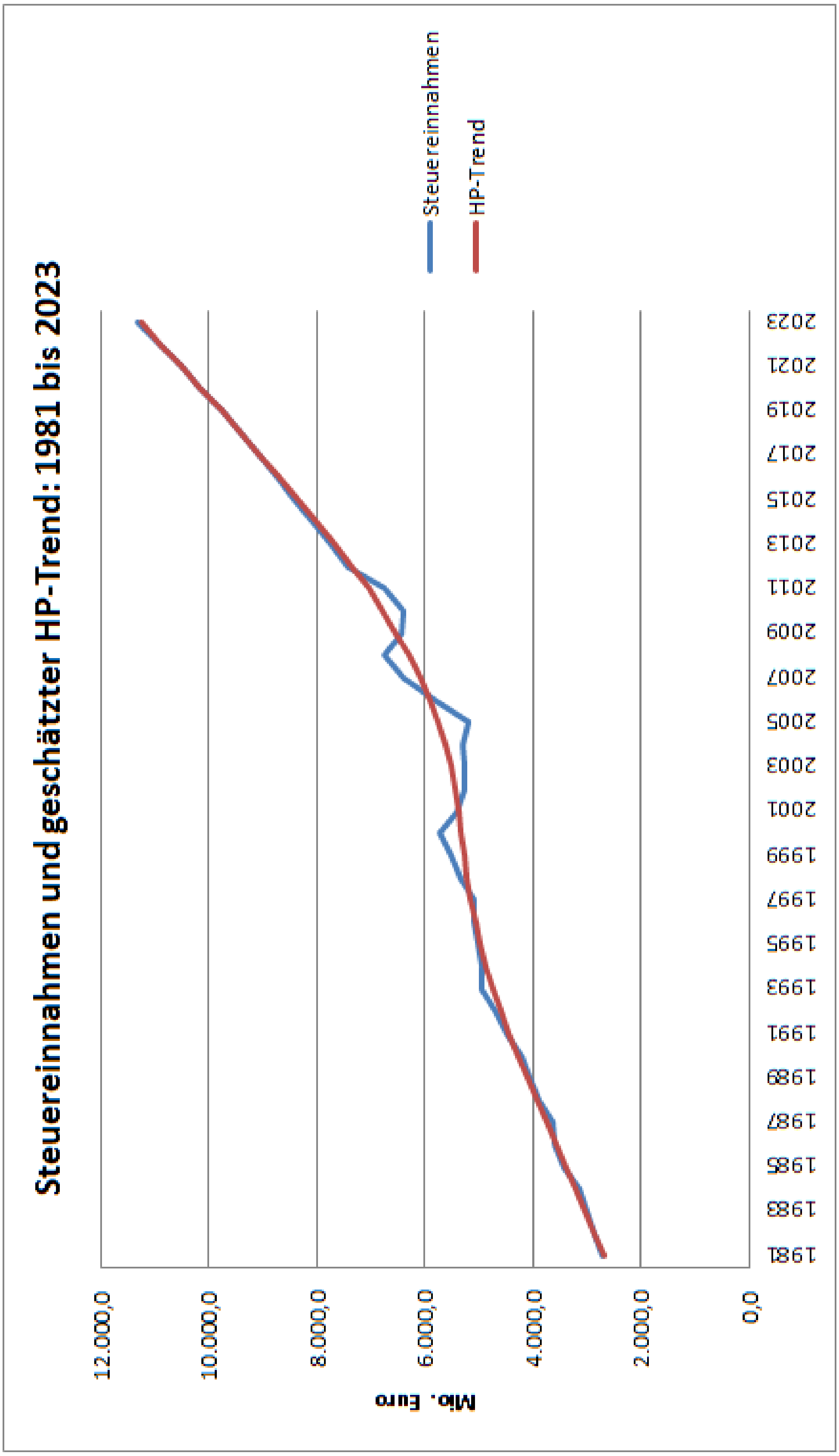

Abbildung 1: Steuereinnahmen und geschätzter HP Trend auf Basis der extrapolierten Steuereinnahmen unter Berücksichtigung der aktuellen Projektionen des Arbeitskreises Steuerschätzungen sowie eigener Projektionen: 1981 bis 2023, eigene Berechnungen.

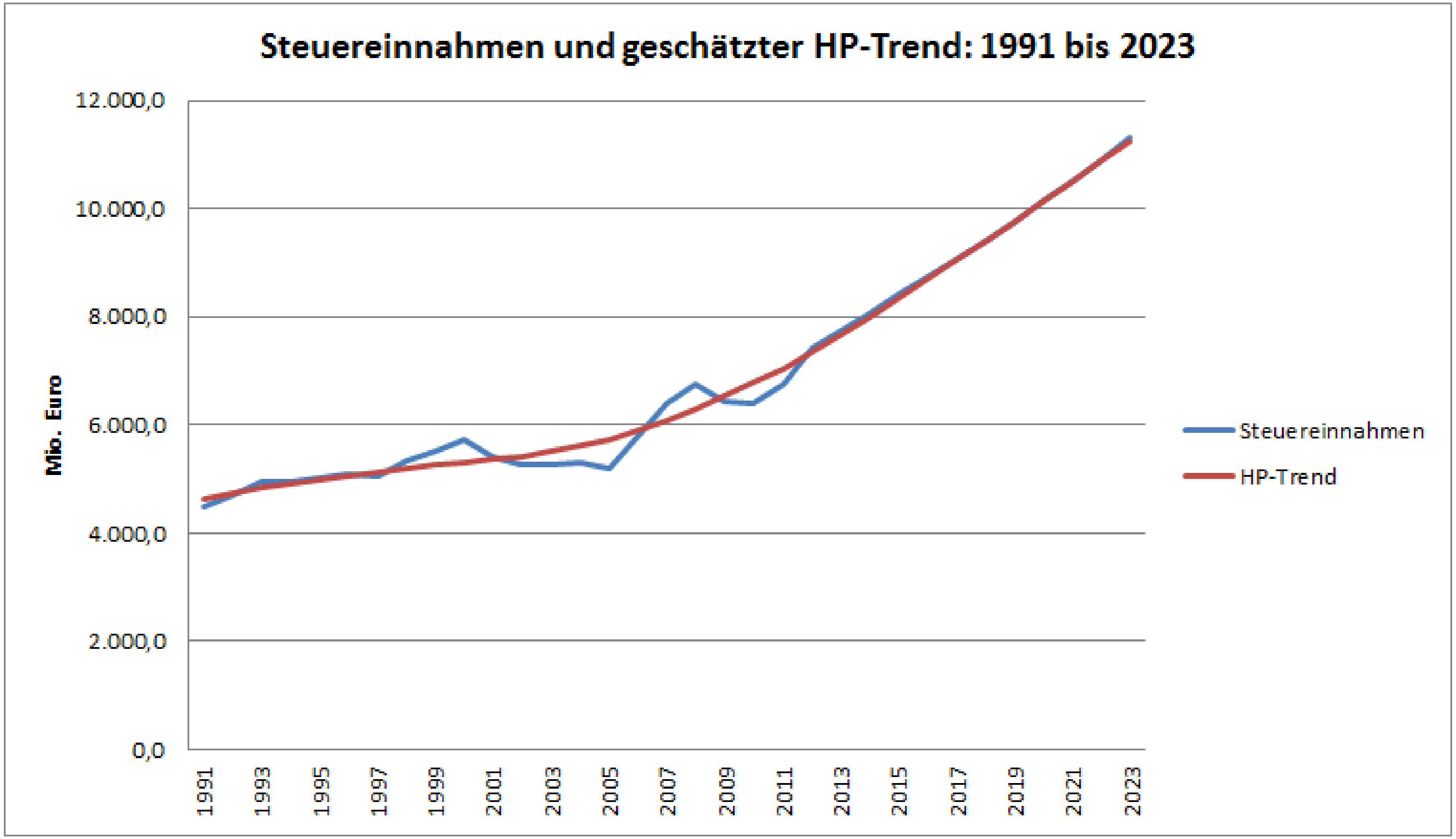

Abbildung 2: Steuereinnahmen und geschätzter HP Trend auf Basis der extrapolierten Steuereinnahmen unter Berücksichtigung der aktuellen Projektionen des Arbeitskreises Steuerschätzungen sowie eigener Projektionen: 1991 bis 2023, eigene Berechnungen.

Tabelle 2

Ergebnisse: 1981 bis 2023 (mit AKS Projektionen)

Jahr	**Einnahmen**	**HP-Trend**	**Wachstumsrate HP-Trend**	**Konjunkturkomponente**
1981	2710, 20	2674, 90		35, 30
1982	2843, 40	2854, 38	6, 71	−10, 98
1983	3001, 60	3034, 22	6, 30	−32, 62
1984	3139, 20	3214, 65	5, 95	−75, 45
1985	3431, 50	3395, 60	5, 63	35, 90
1986	3591, 90	3576, 22	5, 32	15, 68
1987	3626, 00	3756, 04	5, 03	−130, 04
1988	3893,50	3934,74	4, 76	−41, 24
1989	4064,80	4110,69	4,47	−45, 89
1990	4199,40	4281,85	4,16	−82, 45
1991	4473,70	4445,75	3,83	27, 95
1992	4706,80	4599,05	3,45	107, 75
1993	4941,30	4738,72	3,04	202, 58
1994	4961,50	4862,79	2,62	98, 71
1995	5033,20	4971,34	2,23	61, 86
1996	5102,90	5065,42	1,89	37, 48
1997	5074,20	5146,69	1,60	−72, 49
1998	5338,00	5217,20	1,37	120, 80
1999	5528,70	5278,27	1,17	250, 43
2000	5739,80	5332,43	1,03	407, 37
2001	5393,80	5384,72	0,98	9, 08
2002	5271,00	5444,23	1,11	−173, 23
2003	5253,60	5520,17	1,39	−266, 57
2004	5300,10	5619,99	1,81	−319, 89
2005	5211,30	5748,51	2,29	−537, 21
2006	5804,30	5907,32	2,76	−103, 02
2007	6404,00	6092,64	3,14	311, 36
2008	6752,40	6299,68	3,40	452, 72
2009	6434,60	6526,75	3,60	−92, 15
2010	6406,00	6776,69	3,83	−370, 69
2011	6759,70	7051,40	4,05	−291, 70
2012	7412,00	7349,11	4,22	62, 89
2013	7737,00	7665,11	4,30	71, 89
2014	8067,00	7995,31	4,31	71, 69
2015	8420,00	8336,37	4,27	83, 63
2016	8748,00	8685,63	4,19	62, 37
2017	9061,00	9041,29	4,09	19, 71
2018	9409,00	9402,17	3,99	6, 83
2019	9768,05	9767,29	3,88	0, 77
2020	10134,12	10135,72	3,77	−1, 60
2021	10511,95	10506,56	3,66	5, 38
2022	10904,77	10878,89	3,54	25, 88
2023	11313,08	11251,83	3,43	61, 25

Ergebnisse der Projektionen der Steuereinnahmen unter Berücksichtigung der AKS Projektionen (in Mio. Euro), der HP-Trendschätzungen (in Mio. Euro) und deren Wachstumsrate (in %) sowie der resultierenden Konjunkturkomponenten (in Mio. Euro), Eigene Berechnungen.

Tabelle 3

Ergebnisse: 1991 bis 2023 (mit AKS Projektionen)

Jahr	Einnahmen	HP-Trend	Wachstumsrate HP-Trend	Konjunkturkomponente
1991	4473,70	4650,41	0,00	$-176,71$
1992	4706,80	4739,82	1,92	$-33,02$
1993	4941,30	4827,48	1,85	$113,82$
1994	4961,50	4911,26	1,74	$50,24$
1995	5033,20	4990,23	1,61	$42,97$
1996	5102,90	5063,91	1,48	$38,99$
1997	5074,20	5132,29	1,35	$-58,09$
1998	5338,00	5195,72	1,24	$142,28$
1999	5528,70	5253,99	1,12	$274,71$
2000	5739,80	5308,30	1,03	$431,50$
2001	5393,80	5362,61	1,02	$31,19$
2002	5271,00	5425,18	1,17	$-154,18$
2003	5253,60	5504,59	1,46	$-250,99$
2004	5300,10	5607,88	1,88	$-307,78$
2005	5211,30	5739,58	2,35	$-528,28$
2006	5804,30	5901,13	2,81	$-96,83$
2007	6404,00	6088,70	3,18	$315,30$
2008	6752,40	6297,49	3,43	$454,91$
2009	6434,60	6525,85	3,63	$-91,25$
2010	6406,00	6776,69	3,84	$-370,69$
2011	6759,70	7051,98	4,06	$-292,28$
2012	7412,00	7350,02	4,23	$61,98$
2013	7737,00	7666,15	4,30	$70,85$
2014	8067,00	7996,37	4,31	$70,63$
2015	8420,00	8337,34	4,26	$82,66$
2016	8748,00	8686,48	4,19	$61,52$
2017	9061,00	9041,99	4,09	$19,01$
2018	9409,00	9402,71	3,99	$6,29$
2019	9768,05	9767,67	3,88	$0,38$
2020	10134,12	10135,95	3,77	$-1,83$
2021	10511,95	10506,65	3,66	$5,30$
2022	10904,77	10878,83	3,54	$25,93$
2023	11313,08	11251,63	3,43	$61,45$

Ergebnisse der Projektionen der Steuereinnahmen unter Berücksichtigung der AKS Projektionen (in Mio. Euro), der HP-Trendschätzungen (in Mio. Euro) und deren Wachstumsrate (in %) sowie der resultierenden Konjunkturkomponenten (in Mio. Euro), Eigene Berechnungen.

Eidesstattliche Erklärung

Hiermit erkläre ich an Eides statt, dass ich meine Doktorarbeit "*Empirical Investigations of Current Monetary and Fiscal Policy Issues*" selbstständig und ohne fremde Hilfe angefertigt habe und dass ich alle von anderen Autoren wörtlich übernommenen Stellen, wie auch die sich an die Gedanken anderer Autoren eng anlehnenden Ausführungen meiner Arbeit, besonders gekennzeichnet und die Quellen nach den mir angegebenen Richtlinien zitiert habe.

Datum Unterschrift